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Impact of the announcement and implementation of the UK Soft Drinks Industry Levy on sugar content, price, product size and number of available soft drinks in the UK, 2015-19: a controlled interrupted time series analysis

Short title: The Soft Drinks Industry Levy's impact on sugar, price, size and number of drinks

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Abbreviations:

CITS	Controlled Interrupted Time Series
SDIL	Soft Drinks Industry Levy
SSB	Sugar Sweetened Beverage

Abstract

Background: Dietary sugar, especially in liquid form, increases risk of dental caries, adiposity and type 2 diabetes. The UK Soft Drinks Industry Levy (SDIL) was announced in March 2016 and implemented in April 2018 and charges manufacturers and importers at £0.24 per litre for drinks with over 8g sugar per 100ml (high levy category), £0.18 per litre for drinks with 5 to 8g sugar per 100ml (low levy category) and no charge for drinks with less than 5g sugar per 100ml (no levy category). Fruit juices and milk-based drinks are exempt. We measured the impact of the SDIL on price, product size, number of soft drinks on the marketplace, and the proportion of drinks over the lower levy threshold of 5g sugar per 100ml.

Methods and Findings: We analysed data on a total of 209,637 observations of soft drinks over 85 time points between September 2015 and February 2019, collected from the websites of the leading supermarkets in the UK. The dataset was structured as a repeat cross-sectional study. We used controlled interrupted time series to assess the impact of the SDIL on changes in level and slope for the four outcome variables. Equivalent models were run for potentially levy-eligible drink categories (‘intervention’ drinks) and levy-exempt fruit juices and milk-based drinks (‘control’ drinks). Observed results were compared with counterfactual scenarios based on extrapolation of pre-SDIL trends.

We found that in February 2019, the proportion of intervention drinks over the lower levy sugar threshold had fallen by 33.8 percentage points (95% confidence intervals: 33.3, 34.4, $p < 0.001$). The price of intervention drinks in the high levy category had risen by £0.075 (£0.037, £0.115, $p < 0.001$) per litre – a 31% pass through rate – whilst prices of intervention drinks in the low levy category and no levy category had fallen and risen by smaller amounts, respectively. Whilst the product size of branded high levy and low levy drinks barely changed after implementation of the SDIL (-7ml (-23ml, 11ml) and 16ml (6ml, 27ml) respectively), there were large changes to product size of own-brand drinks with an increase of 172ml (133ml, 214ml) for high levy drinks and a decrease of 141ml (111ml, 170ml) for low levy drinks. The number of available drinks that were in the high levy category when the SDIL was announced was reduced by 3 (-6, 12) by the implementation of the SDIL. Equivalent models for control drinks provided little evidence of impact of the SDIL. These results are not sales weighted, so do not give an account of how sugar consumption from drinks may have changed over the time period.

Conclusions: The results suggest that the SDIL incentivised many manufacturers to reduce sugar in soft drinks. Some of the cost of the levy to manufacturers and importers was passed on to consumers as higher prices, but not always on targeted drinks. These changes could reduce population exposure to liquid sugars and associated health risks.

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Author summary

Why was this study done?

- In March 2016, the UK Government announced the Soft Drinks Industry Levy (SDIL) – a tax on soft drinks that contain more than 5g sugar per 100ml. Fruit juices and milk-based drinks are exempt from the levy. The stated aim of the SDIL was to encourage the soft drinks industry to improve the healthiness of the drinks they produce, by reducing sugar content or reducing portion sizes. The SDIL was implemented in April 2018.
- This study measures the impact of the SDIL on the soft drinks that are available to buy in the UK, to evaluate whether the SDIL achieved its aim of influencing industry practice.

What did the researchers do and find?

- We used data on 209,637 observations of soft drinks available from UK supermarket websites at 85 time points between September 2015 and February 2019.
- At each time point, we measured the percentage of drinks with sugar levels greater than 5g per 100ml, the price of drinks, the volume at which they are sold, and the number of different drinks available to purchase, and compared these with estimates of what would have happened if the SDIL was not introduced.
- We found changes to sugar levels in drinks. The percentage of drinks with sugar over 5g per 100ml fell from 49% to 15% over the time period. There was little change in the product size or the number of products available to consumers. The price of high sugar drinks increased after the implementation of the SDIL, but only by one third of the amount of the tax.

What do these findings mean?

- The results show that the SDIL was associated with a considerable impact on the soft drinks industry, particularly with regard to the amount of sugar in soft drinks. The SDIL was not associated with a reduction in the size of the soft drinks marketplace.
- These results are not weighted by sales of soft drinks, so we are not able to estimate the impact of these changes on sugar consumption.

Introduction

Free sugars have been shown to be associated with obesity and type 2 diabetes [1,2], especially when consumed in liquid form [3,4]. Consumption of sugar sweetened beverages (SSBs) increases body weight in children [5,6], and has been associated with obesity [7,8], diabetes [9,10,11], hypertension [12] and cardiovascular disease [9,13] in adults. An estimated 3.6% of diabetes cases in the UK (and 8.7% of cases in the US) are attributable to SSB consumption [14] – a condition that presently costs the National Health Service (NHS) around £10 billion a year [15].

In October 2015, in response to the Health Select Committee inquiry on Childhood Obesity [16], Public Health England published a report listing recommendations for reducing sugar consumption in children, including a tax on SSBs [17]. George Osborne, then Chancellor of Exchequer, announced in his budget of 16th March 2016 that the Government would introduce a UK Soft Drinks Industry Levy (SDIL) to be implemented on 6th April 2018 [18], allowing two years for manufacturers to prepare for the levy by reformulating drinks, reducing product sizes, or removing / introducing products from / to the marketplace. The SDIL is a levy on manufacturers and importers of soft drinks based on total sales of drinks aimed at influencing industry behaviour. This distinguishes it from most soft drink taxes introduced elsewhere [19], which are normally excise taxes, aimed at increasing price for the end consumer, with the intention of reducing demand for SSBs. To incentivise reformulation of sugar levels, the SDIL is a two-tiered levy: drinks over 8g of sugar per 100ml are levied at a rate of £0.24 per litre (*higher levy tier*); between 5 and 8g of sugar per 100ml, drinks are levied at a rate of £0.18

per litre (*lower levy tier*). Drinks with less than 5g sugar per 100ml are not levied (*no levy tier*) [20]. Soft drinks that are 100% fruit juice, at least 75% milk (or a milk replacement), contain greater than 1.2% alcohol (or are an alcoholic beverage replacement), or are produced or distributed by manufacturers and importers with UK sales less than 1 million litres per year are exempt from the SDIL, irrespective of sugar content. These rates were announced in March 2016 but not confirmed until 27th February 2017 in a pre-budget statement. A more detailed description of the policy objectives for the SDIL can be found elsewhere [21].

Previous evaluations of soft drink taxes have focussed on their impact on price and consumer purchasing behaviour [22,23,24,25], but have not evaluated their impact on sugar content in drinks, product sizes and product diversity within the marketplace. We hypothesised that the SDIL would have multiple impacts on the UK food and drink system [26], and here we report on the impact of the announcement (16th March 2016) and implementation (6th April 2018) of the SDIL on the proportion of soft drinks with sugar levels above levy thresholds, their price, the volume in which they are sold, and the number of soft drinks in supermarkets. We present results separately for 'branded' and 'own-brand' products (here we define 'own-brand' products as those manufactured and branded by supermarket, and 'branded' products as all other drinks) as they occupy different places in the soft drinks marketplace. Consumers of own-brand products tend to be more motivated by price than by quality and perception of own-brands influence consumers' perception of the supermarket as a whole [27-28]. Manufacturers of branded and own-brand products therefore have different motivations and could react to the SDIL differently.

Methods

Outcome measures

Using a time-stamped dataset of observations of soft drinks available in UK supermarkets between September 2015 and February 2019, we assessed whether the announcement and implementation of the SDIL had an impact on the following measures:

- The proportion of available drinks with sugar content greater than 5g per 100ml (the threshold over which the levy applies. An equivalent analysis considering the proportion of drinks with sugar content greater than or equal to 8g per 100ml – the higher levy threshold – is reported in S1 Appendix)
- The mean price (£ per 100ml) of available soft drinks
- The mean product size (ml) of available soft drinks
- The number of soft drinks available for purchase from UK supermarkets. Here we refer to the different options available to the consumer, rather than the number of sales or the number of items available on supermarket shelves.

For the price, product size and product diversity analyses, we stratified our results into three groups by sugar content: less than 5g sugar per 100ml (where no levy applies); 5-<8g sugar per 100ml (where the lower levy rate applies); greater than or equal to 8g sugar per 100ml (where the higher levy rate applies). Soft drinks appearing in different product sizes or in different supermarkets were included as independent observations in the study dataset.

Study design

We had no unique identifier for the soft drinks that were included in the analysis, and therefore we were not able to link all observations at different time points. Therefore, we were unable to create a panel series, and structured our dataset as a repeat cross-sectional design. Within this structure, we used controlled interrupted time series (CITS) analysis [29], with two intervention points: the announcement (16th March 2016) and the implementation (6th April 2018) of the SDIL. The units of analysis for the CITS were observations of all soft drinks identified from supermarkets at 85 time points between September 2015 and February 2019 (see further below). 'Soft drinks' were defined as all edible liquids (either sold ready to drink or to be reconstituted from liquid concentrates) excluding soups, alcoholic beverages (and non-alcoholic versions), cow's milk, dried drinks (e.g. milkshake powder, instant coffee), bottled water or flavourings that need the addition of water (e.g. tea bags).

For each of the outcome measures, we conducted separate analyses on what we have called 'intervention' and 'control' drinks for brevity. 'Intervention' drinks consisted of all soft drinks except SDIL-exempt fruit juices and milk-based drinks. This set includes drinks that do not attract levy payments, as they have sugar levels below the minimum threshold of 5g/100ml (e.g. 'diet' variants of popular drink brands), but represent a category into which levy-eligible drinks might fall following reformulation. 'Control' drinks consist of soft drinks that were exempt from the SDIL due to being 100% fruit juice, milk-based or a milk alternative (regardless of sugar content). The control series was chosen as it was assumed that trends over time in this group would not be affected by the SDIL. Demonstrating this alongside effects in the intervention series would show specificity of results, strengthening the evidence that any observed relationship is causal [29].

The decision regarding how to categorise soft drinks that are neither subject to exemptions, nor have sugar levels above the minimum threshold of 5g/100ml is not straightforward. These drinks are not subject to the levy, so could be regarded to be equivalent to drinks from exempt categories. However, we included such drinks in the intervention series as manufacturers could react to the SDIL by reducing sugar content of drinks, thereby moving drinks from categories that are taxed into categories that are not. If our study design included these non-taxed categories in the control series then we would allow drinks to migrate from the intervention to the control series over time, which would violate our assumption that the SDIL does not affect the control series.

To report the impact of the SDIL on trends, we estimated counterfactual scenarios where pre-SDIL trends in the variable of interest were extrapolated to simulate the likely trajectory in the absence of the SDIL, and then we estimated the difference between the observed measures from the regression models and counterfactual scenarios at four time points: 50 days post-announcement (5th May 2016); 50 days pre-implementation (15th February 2018); 50 days post-implementation (26th May 2018); and the end of the current dataset (17th February 2019, which is 317 days post-implementation). To estimate confidence intervals around the differences, we compared the 95% lower and higher confidence intervals from the observed results with point estimates from the counterfactual. The chosen timepoints for displaying results are arbitrary. The complete set of regression model results are provided in S2 Appendix allowing for estimation of results at any timepoint.

Data

Fig 1 provides a data flowchart for the separate analyses described in this manuscript. We compiled data from two sources. Firstly, we used data collected from the websites of the six leading UK supermarkets (Asda, Sainsbury's, Tesco, Morrisons, Ocado and Waitrose) that together account for 74% of UK grocery sales [30]. We collected data for this analysis using a web-scraping and data processing software and database platform called foodDB, which has run continuously since November 2017. Full details of the methods of data collection using this tool are provided elsewhere [31]. Briefly, foodDB software collects and processes data automatically on over 99% of all food and drink products available for purchase on supermarket websites each week, including product name, nutritional information, ingredients, product size, price and whether or not the product is on promotion. A validation exercise comparing foodDB data with equivalent data collected from 295 randomly selected products in real life stores showed high correlation between the two datasets for price and sugar levels and no evidence of systematic bias in comparison of the two datasets (S3 Appendix). The current dataset consisted of weekly data from foodDB from 26th November 2017 until 17th February 2019, consisting of 64 time points and 302,473 observations. Soft drinks were dropped from the dataset if they had missing data on price or product size (there were no missing data on other study variables). Due to changes in UK supermarket website design, on some occasions the foodDB software fails to make a complete data capture. We removed these occasions from the analysis by excluding all data collected in weeks where the total number of soft drinks collected by foodDB was less than 90% of the weekly average in the rest of the dataset. After exclusions, the foodDB dataset consisted of 277,258 observations over 58 time points.

Fig 1: Data flowchart

INSERT FIGURE 1 HERE

The second dataset provided us with data from prior to the announcement of the SDIL. We used data from 92,883 observations of soft drinks at 38 monthly time points, from 1st August 2015 to 1st September 2018 acquired from Brandview, a commercial company that collects product data using methods similar to those used in foodDB on all products available from Tesco, Sainsbury’s and Asda. After excluding observations with missing price or product size data and excluding time points where data collection was less than 90% of average, the BrandView dataset provided 88,622 observations over 37 time points (NB: the removed time point was from the first month, limiting the BrandView dataset to September 2015 onwards).

We categorised all observations as 'intervention' or 'control' based on supermarket categorisation and manual inspection of product names, using equivalent methods for each dataset.

Statistical methods

We used a data-driven approach to build regression models with the aim of reproducing time trends observed in the datasets and isolating the impact of the announcement and implementation of the SDIL. We were not aiming to infer the size of the effect of a sugary drink tax on an average soft drink. This influences our modelling strategy, for example we did not include product-level characteristics as confounding variables in the CITS models. For all outcome measures we hypothesised that the SDIL could impact on both the level and the slope of the trend, and thereby included dummy variables representing the interventions and interaction terms in our regression models (i.e. a 'level and slope change analysis' [32]) and we used likelihood ratio tests to identify whether including both level and slope changes improved model fit beyond including level change alone (with a threshold for decision making of $p = 0.05$). Bernal et al. [29] state that two types of CITS model can be deployed: separate analysis of the intervention and the control series, or a single model incorporating both series. The former model estimates the difference between before and after the event in the intervention series, and uses the control series as a plausibility check – the event should only impact the intervention series and effects found in the control series could be evidence of unmeasured confounding variables. The latter model estimates the *difference in difference* between the intervention and the control series directly. Here, we use the former approach as due to the population-level nature of the SDIL it was not possible to acquire location-based controls (i.e. data on the same drinks but sold in supermarkets unaffected by the SDIL). For all outcome measures, regression models were run on the control drinks that included identical parameters to the equivalent models on intervention drinks. All analyses were conducted in R version 3.4.4.

For each analysis, we first observed trends in the raw data which informed the model building strategy. Where non-linear trends were observed, we included polynomial regression parameters, testing each additional parameter for improved model fit using likelihood ratio tests. Because of the very large number of possible models that could be tested, we restricted exploration of non-linear effects only to time periods where trends in the non-modelled data clearly deviated from linearity. Where seasonality was observed, we included dummy variables to capture this. The specific methods used for each analysis are described below.

Comparison of datasets

S3 Appendix describes the methods and results used to check for consistency between the foodDB and BrandView datasets. These assessments were based on a comparison dataset with overlapping data from November 2017 to September 2018. To ensure comparability, all data from Waitrose, Ocado and Morrisons were removed from the comparison dataset.

Reformulation

To conduct analyses of the impact of the SDIL on sugar content of drinks, overlapping data from BrandView were removed from the dataset constructed for the comparison of the BrandView and foodDB data, resulting in a total of 209,637 observations of soft drinks from three supermarkets over 85 time points between September 2015 and February 2019. We built logistic regression models with dummy variables for the announcement and implementation of the SDIL.

Price

Observation of trends in the raw data showed little evidence that the announcement of the SDIL had any impact on price of soft drinks. Therefore, the price analyses were conducted using the foodDB dataset only. For the price variable, we used the price presented to the consumer for a single item purchase, which included reductions due to price promotions (e.g. 10% off), but not volume-based promotions (e.g. buy one get one free). We adjusted prices for an annual inflation rate of 1.7% [33], presenting all prices as of February 2019. Visual inspections of p-p plots suggested that the price variable was not normally distributed and contained a long tail of high priced drinks. To convert to normality, we first excluded outlying drinks with a price greater than £1 per litre and then log-transformed the variable. We conducted linear regression modelling on the log-transformed price variable. To protect against confounding of the results by drinks moving between SDIL tiers over time (i.e. by reducing sugar content), we categorised drinks into high levy, low levy and no levy categories on the basis of the category that they were in *after* the implementation of the SDIL. To do this, we matched drinks in the dataset on the basis of name and excluded all drinks that could not be matched. Inspection of trends revealed that prices of soft drinks were reduced in December as Christmas promotions kicked in – we therefore included a dummy variable to indicate December in the price analyses. The price analysis dataset contained 240,048 observations of soft drinks from six supermarkets over 58 time points.

Product size

For the product size variable we did not exclude drinks sold in multipacks, and for these took the product size to be the total volume of all individual drinks in the multipack combined. For similar reasons to the price analysis, we restricted the analysis to the foodDB dataset, excluded outliers and log-transformed the product size variable, and matched drinks to categorise them on the basis of levy category after implementation of the SDIL. The product size analysis dataset contained 239,739 observations of soft drinks from six supermarkets over 58 time points.

Number of soft drinks

For the number of soft drinks analysis we restricted the analysis to the foodDB dataset for similar reasons to the price and product size analyses. We matched the drinks by name and categorised each drink on the basis of the levy category for its last appearance in the dataset. We collapsed the dataset on time point and conducted linear regression analyses on the aggregated 'number of drinks' variable. The collapse of the dataset allowed us to explore whether temporal autocorrelation was present and how it affected the analyses. To do this, we included a lag term (the number of drinks at the previous time point) in the model. The number of drinks analysis consisted of 58 time points for both intervention and control drinks, with aggregated data from six supermarkets at each time point.

Changes to published protocol

We made the following changes to the pre-specified protocol ([26] and reproduced in S4 Appendix). We used a different time frame for the analysis which includes an earlier than anticipated initial date, due to our acquisition of data pre-November 2017 from BrandView. We will undertake further analyses up to the original proposed end date of April 2020 once data are available. For now we present analyses up to approximately one year post-implementation of the SDIL, in order to provide timely evidence of the effects of the levy. The protocol states that we will analyse the impact of the SDIL on mean sugar content of drinks – upon reflection we considered that a binary classification of the data (drinks above or below the lower levy sugar threshold) was a more appropriate way to model manufacturer response to the SDIL. The pre-defined analysis using mean sugar level is reported in S5 Appendix for completeness. In the protocol, we proposed using alcoholic drinks as the control series – this was altered as most alcoholic drinks do not report sugar content.

Results

Table 1 shows descriptive statistics comparing the main outcome variables between intervention and control drinks in each dataset. Further descriptive statistics for the combined BrandView and foodDB dataset are available in S3 Appendix. Average sugar levels and price were higher in control drinks, but the average product size was smaller (p < 0.001 in all cases). There were nearly 50% more intervention than control drinks in the datasets.

Table 1: Descriptive statistics of sugar levels, price, product size and number of soft drink observations

	N[1]	Median	IQR	P[2]
Sugar (g per 100ml)				
Higher levy tier intervention drinks	*26,755*	*10.6*	*9.8 – 11.6*	
Lower levy tier intervention drinks	*13,857*	*7.0*	*6.3 – 7.5*	
No levy tier intervention drinks	*92,837*	*0.5*	*0.0 – 4.3*	
All intervention drinks	133,449	4.2	0.2 – 7.1	
All control drinks	76,188	8.2	3.4 – 10.0	<0.001
Price (p per 100ml)[3]				
Higher levy tier intervention drinks	*12,813*	*25.4*	*20.2 – 36.5*	
Lower levy tier intervention drinks	*12,535*	*33.8*	*26.9 – 40.7*	
No levy tier intervention drinks	*111,626*	*14.2*	*9.0 – 24.0*	
All intervention drinks	136,974	17.3	10.1 – 27.4	
All control drinks	103,074	21.3	14.3 – 37.5	<0.001
Product size (ml)				
Higher levy tier intervention drinks	*12,111*	*750*	*497 – 1006*	
Lower levy tier intervention drinks	*12,613*	*749*	*500 – 781*	
No levy tier intervention drinks	*109,726*	*1000*	*548 – 1974*	
All intervention drinks	134,450	1000	500 – 1842	
All control drinks	105,289	950	593 – 1000	<0.001
Number per week				
Higher levy tier intervention drinks	*58*	*256*	*252 – 291*	
Lower levy tier intervention drinks	*58*	*298*	*287 – 311*	
No levy tier intervention drinks	*58*	*2274*	*2245 – 2319*	
All intervention drinks	58	2862	2795-2902	
All control drinks	58	1971	1946-2010	<0.001

[1] For 'sugar', 'price' and 'product size', this represents the total number of observations over all time points included in the analyses. For 'number per week', all observations are collapsed in each time point, so this represents the number of time points in the analyses. [2] From Wilcoxon rank sum test comparing intervention and control drinks. [3] Adjusted to February 2019 prices. IQR = Interquartile range. Note that for price and product size, the categorisation by levy tier is based on the categorisation of products after implementation of

the levy, for number per week it is based on the last observation in the dataset, and for sugar it is based on the sugar level at the point of observation.

Table 2 compares the proportion of drinks over the lower levy sugar threshold with the counterfactual scenario in which pre-announcement trends were extrapolated, with the trend for all intervention and control drinks shown in Fig 2. The proportion of intervention drinks over the lower levy sugar threshold reduced after the announcement of the SDIL only slowly at first, but with rapid changes just prior to the implementation. Just 50 days before the implementation, intervention drinks with enough sugar to be included in the levy had fallen by 19.5 (95% CI: 18.9, 20.1) percentage points – 50 days after implementation intervention drinks had fallen by 30.7 (30.3, 31.2) percentage points. As of February 2019, only 15.4% (14.8%, 15.9%) of intervention soft drinks were above the lower levy sugar threshold. Equivalent models for the control drinks found little evidence of impact of the announcement or implementation of the SDIL on percentage of drinks above each levy threshold (see S2 Appendix for all model results). The pattern of sugar reduction in own-brand and branded drinks was very different – for own-brand drinks, sugar levels were already falling before the announcement of the SDIL, but these falls accelerated after the announcement. By the time of the implementation of the SDIL, only 6.9% (6.3%, 7.6%) of own-brand intervention drinks remained over the lower levy sugar threshold and further sugar reduction stalled. For branded drinks, there was a large fall in the proportion of drinks over the lower levy sugar threshold at the point of the implementation, which resulted in a 43.5 (42.9, 44.1) percentage point fall in the number of branded intervention drinks over the lower levy sugar threshold by February 2019, leaving only 17.6% (17.0%, 18.2%) of branded drinks above the lower levy sugar threshold..

Table 2: Difference between observed and counterfactual (extrapolation of pre-announcement trends) percentage of soft drinks over the lower levy sugar threshold

		Difference in percentage[1] of drinks over lower levy sugar threshold (95% confidence intervals)			
	Percentage over lower levy threshold before announcement	5th May 2016(50 days post-announcement)	15th February 2018 (50 days pre-implementation)	26th May 2018(50 days post-implementation)	17th February 2019 (End of dataset)
All intervention drinks	51.7 (50.9, 52.6)	-0.1 (-1.3, 1.1)	-19.5 (-20.1, -18.9)	-30.7 (-31.2, -30.3)	-33.8 (-34.4, -33.3)
Branded intervention drinks	57.9 (57.0, 59.0)	-1.1 (-2.4, 0.3)	-23.8 (-24.5, -23.1)	-38.3 (-38.9, -37.8)	-43.5 (-44.1, -42.9)
Own-brand intervention drinks	34.8 (33.2, 36.4)	2.5 (0.3, 4.7)	-11.5 (-12.2, -10.7)	-12.2 (-12.9, -11.5)	-9.4 (-10.2, -8.6)
All control drinks	68.1 (66.8, 69.3)	0.6 (-1.0, 2.2)	-5.8 (-6.6, -5.1)	-6.9 (-7.6, -6.2)	-7.9 (-8.9, -7.0)

[1] Results are presented as percentage point differences compared to the counterfactual (extrapolation of pre-announcement trend).

Fig 2: Proportion of soft drinks over the lower levy sugar threshold

INSERT FIGURE 2 HERE

Table 3 shows the results of the price analysis, with Fig 3 showing the trend for intervention and control drinks, separately for branded and own-brand drinks. Branded drinks passed on about half of the levy on higher levy tier drinks (i.e. the price increase on these drinks was half of the levy rate), whilst the prices of lower levy tier drinks reduced after implementation of the SDIL. In contrast, own-brand drinks saw large changes in price with higher levy tier drinks reducing in price by 62.5p per L (52.4, 72.1) and lower levy tier drinks increasing by 68.6p per L (56.9, 81.1) – Fig 2 shows how the price point for these two categories converged after the implementation of the SDIL.

Table 3: Difference between the observed and counterfactual (extrapolation of pre-implementation trends) in prices of soft drinks as of 26th May 2018 (50 days post-implementation)

	Mean price before implementation, pence (p) per litre (95% CI)[1]	Difference in price, pence (p) per litre (95% CI)[1]	Pass-on rate[2]
All drinks			
Higher levy tier intervention drinks	251.0 (240.3, 262.2)	7.5 (3.7, 11.5)	31% (15%, 48%)
Lower levy tier intervention drinks	319.3 (305.8, 333.4)	-10.7 (-15.3, -6.0)	-59% (-85%, -33%)

No levy tier intervention drinks	135.4 (127.7, 143.6)	3.6 (2.6, 4.7)	n/a
Control drinks	227.5 (215.7, 239.9)	-1.5 (-3.0, 0.1)	n/a
Branded drinks			
Higher levy tier intervention drinks	250.5 (239.7, 261.8)	11.8 (7.7, 15.9)	49% (32%, 66%)
Lower levy tier intervention drinks	336.5 (323.6, 350.0)	-17.4 (-22.0, -12.8)	-97% (-122%, -71%)
No levy tier intervention drinks	162.9 (154.9, 171.4)	2.6 (1.4, 3.8)	n/a
Control drinks	269.3 (256.6, 282.6)	-4.1 (-5.9, -2.2)	n/a
Own-brand drinks			
Higher levy tier intervention drinks	268.8 (260.8, 277.1)	-62.5 (-72.1, -52.4)	-260% (-300%, -218%)
Lower levy tier intervention drinks	123.2 (118.8, 127.8)	68.6 (56.9, 81.1)	381% (316%, 451%)
No levy tier intervention drinks	70.7 (67.1, 74.5)	-0.8 (-1.9, -0.3)	n/a
Control drinks	122.8 (118.6, 127.1)	0.1 (-1.1, 1.4)	n/a

[1] Adjusted to February 2019 prices. [2] Higher levy tier drinks are levied at £0.24 (24p) per litre, lower levy tier drinks are levied at £0.18 (18p) per litre, no levy tier drinks and control drinks are not levied. The pass-on rate is the percentage of the levy that was passed to the consumer as a change in price.

Fig 3: Change in price of a) branded and b) own-brand soft drinks by sugar content

INSERT FIGURE 3 HERE

Table 4 shows the results for product size and number of drinks available in supermarkets. For product size, there was very little impact of the SDIL on branded drinks, which showed only small fluctuations in product size after implementation of the SDIL of similar magnitude to variations observed in the control drinks. However, for own-brand drinks we observed a similar convergence as seen in the price analyses – here, drinks levied at the lower level reduced in average product size and drinks levied at the higher rate increased until the average product size in both were similar. For product diversity, the inclusion of lag terms had little impact on model results. The models used for table 4 and reported in S2 Appendix did not account for autocorrelation. We saw little evidence that the SDIL impacted on the number of drinks available in supermarkets – in general products that left were replaced with new products. The largest difference between the observed and counterfactual scenarios was for control drinks, and these results were based on regression models which suggested only very weak evidence of impact of the SDIL (see S2 Appendix).

Table 4: Difference between product size and diversity in product range of soft drinks in the modelled and counterfactual (extrapolation of pre-implementation trends) results as of 26th May 2018 (50 days post-implementation)

	Difference in product size, ml (95% CI)	Difference in number of products available (95% CI)
All drinks		
Higher levy tier intervention drinks	1 (-15, 17)	-3 (-12, 6)
Lower levy tier intervention drinks	13 (3, 23)	-1 (-11, 8)
No levy tier intervention drinks	-2 (-10, 6)	-54 (-120, 11)
Control drinks	4 (0, 8)	-111 (-161, -61)
Branded drinks		
Higher levy tier intervention drinks	-7 (-23, 11)	-10 (-18, -1)
Lower levy tier intervention drinks	16 (6, 27)	2 (-7, 10)
No levy tier intervention drinks	0 (-9, 9)	-13 (-63, 38)
Control drinks	6 (1, 11)	-91 (-131, -51)
Own-brand drinks		
Higher levy tier intervention drinks	172 (133, 214)	6 (5, 7)
Lower levy tier intervention drinks	-141 (-170, -111)	2 (1, 4)
No levy tier intervention drinks	6 (-7, 20)	-42 (-59, -24)
Control drinks	7 (-0, 15)	-20 (-32, -8)

Discussion

The SDIL was associated with a large reduction in the percentage of soft drinks (particularly branded drinks) that are subject to the levy, due to large reductions in the sugar levels of these drinks. There was no evidence for similar reductions in control SDIL-exempt drinks, suggesting that the SDIL was the motivating factor for this change. We found that the levy was not directly passed on to the consumer through commensurate increases in the prices of targeted drinks, but manufacturers and retailers appear to have taken the opportunity to undertake wider revision of their entire soft drink market offer. For example: there were changes in both prices and volumes of drinks; only half of the levy on branded higher levy tier drinks was passed on to consumers, whilst low sugar variants also increased in price; and price points for own-brand higher and lower levy tier drinks converged. Without sales data to weight the results reported here it is not possible to estimate whether the full extent of the levy was passed on to consumers via increases in prices. Our analysis of product size suggested that manufacturers of branded drinks did not react to the SDIL by changing product sizes. However, supermarkets made large changes to their own-brand product sizes of higher and lower levy tier drinks. About 30% of the price per volume increase on own-brand lower levy tier drinks can be accounted for by the reduction in product sizes – an instance of so-called 'shrinkflation' [34]. We did not observe any changes in the number of soft drinks available to consumers as a result of the SDIL.

These results suggest that the SDIL has stimulated decreases of sugar levels of soft drinks. Reductions were due to reformulation of existing products and replacement of drinks with lower sugar varieties. The stimulus for these changes are likely to include both supply and demand factors – manufacturers may be influenced to reduce sugar levels to avoid the levy, or may be prompted by a change in demand for lower sugar soft drinks after the widespread media attention related to the announcement of the levy. Our results also confirm that the SDIL currently only applies to a small percentage of the soft drinks that are available in the UK grocery market – control drinks make up over a third of the available soft drinks, and by February 2019 only 15% of the intervention drinks were being levied (the remaining 85% had sugar levels lower than the levy sugar threshold). The lower levy sugar threshold (5g per 100ml) is set at a higher level than for the majority of jurisdictions that have instituted sugar drink taxes worldwide [35] and our data show that in February 2019, 65% of control drinks contained greater than or equal to 5g sugar per 100ml. After the implementation of the SDIL, we observed a peak in the proportion of intervention drinks with a sugar level between 4.5 and 5.0g per 100ml (see S5 Appendix), suggesting that many manufacturers chose to reformulate to just below this threshold. The second chapter of the UK Government's childhood obesity plan [36] suggests that the SDIL may be extended to milk-based drinks. Our analyses suggest that if manufacturers of milk-based drinks behave similarly, then this extension could prompt reductions in sugar levels. Given the preponderance of drinks with sugar levels just below 5g per 100ml, a gradual lowering of the lower levy sugar threshold, similar to gradual lowering of salt targets in the UK [37], could also have public health benefits. We also observed that the SDIL was associated with increases in price of non-targeted drinks (intervention drinks with sugar levels lower than the lower levy sugar threshold, such as diet variants). This has not previously been observed for other sugary drink taxes implemented elsewhere [22, 24, 25, 38], suggesting that the nature of the levy (a levy on manufacturers and importers based on reported sales, rather than an excise tax on consumers) may have influenced industry behaviour more widely.

The tiered design of the SDIL is also being implemented in other jurisdictions including South Africa, Ireland and Portugal [35] and it is therefore important to establish whether such a design influences the behaviour of manufacturers. We analysed a comprehensive set of data on soft drinks available for purchase in the leading supermarkets in the UK, which provided adequate statistical power for the analyses and generalisability of the results to the UK grocery market. However, due to the non-randomised design of the study it is not possible to rule out the possibility of residual confounding in our analyses. We have demonstrated specificity for some of our results – similar changes in sugar content, price and product size were not shown in the control drinks – which suggests that the results were not confounded by unmeasured variables.

Our results are not sales weighted, so do not give an account of how sugar consumption from drinks may have changed over the time period. We have not been able to include soft drinks that are only available in supermarket chains or other types of retail outlet outside of those included in this analysis, although as the supermarkets included here are the market leaders this is unlikely to be a major limitation. We were not able to identify soft drinks produced or distributed by manufacturers and importers with UK sales less than 1 million litres per year, which were therefore incorrectly included in ‘intervention’ drinks. Data collected from web scraping tools (which is the case for both datasets used in these analyses) only reflect data that are presented in online supermarkets, which may not reflect the in-store environment, although our initial validation exercise on 295 food and drink products show no evidence of systematic bias when collecting data from online supermarkets (S3 Appendix). The data-driven approaches that we have used for the modelling strategy may lead to over-fitted models which can limit the generalisability of these results to other jurisdictions considering introducing a similarly structured levy [39]. Further, our aim was to reproduce trends observed in the UK over the time period studied using a near-comprehensive dataset of drinks available for purchase, but we did not aim to isolate the independent effect of the SDIL on an 'average' drink adjusted for product and supermarket characteristics. As a result, it is unlikely that the magnitude of our results will be generalizable to other jurisdictions considering introducing a similar levy. The control series may not be isolated from effects of the SDIL (e.g. manufacturers may choose to adapt prices of control drinks in response to the SDIL since they are a potential substitute for intervention drinks). Due to the lack of a unique product identifier in the dataset, it was not possible to analyse these data as a panel series, and hence we were unable to account for the autocorrelation structure in any of the analyses with the exception of the 'number of products' analysis.

Other studies have used CITS to evaluate the impact of voluntary soft drink price increases that have been implemented in the UK [40,41] and soft drink taxes implemented elsewhere in the world [23,24,25, 38] and have shown that they have resulted in reduced sales of targeted drinks [42] and that price increases are generally passed on to the consumer on targeted drinks, but not always the full tax - the French soda tax had a differential pass-on rate in different communities, with more deprived areas having large pass-on rates and an average pass-on rate of 40% [38]. To our knowledge, no previous study has evaluated the impact of an economic instrument for stimulating reformulation of soft drinks. A public health campaign to encourage voluntary soft drink reformulation in Austria was shown to result in a 13% increase in the number of drinks under the campaign threshold of 7.4g sugar per 100ml over a seven year period [43], and the voluntary UK salt reduction campaign that began in the mid-2000s has been shown to have reduced salt levels in commonly consumed food groups by 7% between 2006 and 2011 [44] and up to 47% since 2004 for breakfast cereals (albeit based on a small sample) [45]. An evaluation of the UK Public Health Responsibility Deal, which asked food manufacturers to make pledges for reformulation, found that inherent conflicts within the food system limit the ability of voluntary processes to make sizeable impacts [46]. Our results show a much steeper decline in targeted nutrient levels than those that have been observed in the UK and elsewhere, suggesting that economic instruments may be more effective at changing manufacturer behaviour than voluntary public health interventions. Public Health England (PHE) used data provided by a commercial party on sales of soft drinks between 2015 and 2018 and found that there was reduction of 29% in sales-weighted average sugar content of drinks over this time period [47]. A separate analysis found a 30% reduction in sales-weighted sugar levels between 2015 and 2018 [48] using datasets independent from PHE. The PHE analysis differs from ours in three important aspects – they do not account for background trends in sugar levels, their data includes purchases from a wider range of retail outlets, and their results are sales-weighted. Our equivalent analysis is shown in S5 Appendix – we found a 2.13g per 100ml (2.08, 2.18) fall in sugar levels in intervention drinks due to the announcement and implementation of the SDIL – this relates to a 38% reduction from average sugar levels in September-December 2015.

The SDIL incentivised many manufacturers to reduce sugar in soft drinks. Some of the SDIL was passed onto consumers as higher prices, but not always on targeted drinks. These changes could reduce population exposure to sugars and associated health risks. Further work should investigate the impact of the SDIL on consumer behaviour by influencing purchasing and consumption of soft drinks, as has been shown elsewhere in the world [23-25, 49]. The impact of these changes on consumer behaviour, including substitution effects, will be explored as part of our ongoing evaluation of the SDIL, which will also explore the impact of the SDIL on the economy, consumer attitudes, measured short term and modelled long term health outcomes [26].

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The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health and Social Care.

References

1. Vartanian LR, Schwartz MB, Brownell KD. Effects of Soft Drink Consumption on Nutrition and Health: A Systematic Review and Meta-Analysis. Am J Public Health. 2007;97(4): 667-675.

2. Te Morenga L, Mallard S, Mann J. Dietary sugars and body weight: systematic review and meta-analyses of randomised controlled trials and cohort studies. BMJ. 2013;346: e7492.

3. Wang J, Light K, Henderson M, O'Loughlin J, Mathieu ME, Paradis G, et al. Consumption of added sugars from liquid but not solid sources predicts impaired glucose homeostasis and insulin resistance among youth at risk of obesity. J Nutr. 2014;144(1): 81-86.

4. Wang J, Shang L, Light K, O'Loughlin J, Paradis G, Gray-Donald K. Associations between added sugar (solid vs. liquid) intakes, diet quality, and adiposity indicators in Canadian children. Applied Phys, Nutr and Metabolism. 2015;40(8): 835-841.

5. De Ruyter JC, Olthof MR, Seidell JC, Katan MB. A Trial of Sugar-free or Sugar-Sweetened Beverages and Body Weight in Children. NEJM. 2012;367: 1397-1406.

6. Ebbeling CB, Feldman HA, Chomitz VR, Antonelli TA, Gortmaker SL, Osganian SK, et al. A Randomized Trial of Sugar-Sweetened Beverages and Adolescent Body Weight. NEJM. 2012;367: 1407-1416.

7. Malik VS, Pan A, Willett WC, Hu FB. Sugar-sweetened beverages and weight gain in children and adults: a systematic review and meta-analysis. Am J Clin Nutr. 2013;98(4): 1084-1102.

8. Gibson S. Sugar-sweetened soft drinks and obesity: a systematic review of the evidence from observational studies and interventions. Nutr Research Reviews. 2008;21(2): 134-137.

9. Malik VS, Popkin BM, Bray GA, Despres J-P, Hu FB. Sugar-Sweetened Beverages, Obesity, Type 2 Diabetes Mellitus, and Cardiovascular Disease Risk. Circulation. 2010;121: 1356-1364.

10. Hu FB, Malik VS. Sugar-sweetened beverages and risk of obesity and type 2 diabetes: Epidemiologic evidence. Physiology & Behavior. 2010;100(1): 47-54.

11. Malik VS, Popkin BM, Bray GA, Despres J-P, Willett WC, Hu FB. Sugar-Sweetened Beverages and Risk of Metabolic Syndrome and Type 2 Diabetes. A meta-analysis. Diab Care. 2010;33(11): 2477-2483.

12. Chen L, Caballero B, Mitchell DC, Loria C, Lin P-H, Champagne CM, et al. Reducing Consumption of Sugar-Sweetened Beverages Is Associated With Reduced Blood Pressure. A Prospective Study Among United States Adults. Circulation. 2010;121: 2398-2406.

13. Xi B, Huang Y, Reilly KH, Li S, Zheng R, Barrio-Lopez MT, et al. Sugar-sweetened beverages and risk of hypertension and CVD: a dose-response meta-analysis. Br J Nutr. 2015;113(5) :709-717.

14. Imamura F, O'Connor L, Ye Z, Mursu J, Hayashino Y, Bhupathiraju SN, et al. Consumption of sugar sweetened beverages, artificially sweetened beverages, and fruit juice and incidence of type 2 diabetes: systematic review, meta-analysis, and estimation of population attributable fraction. BMJ. 2015;351: h3576.

15. Diabetes UK. The cost of diabetes. London: Diabetes UK; 2014.

16. Health Select Committee. Childhood obesity – brave and bold action. London: Houses of Commons; 2015.

17. Public Health England. Sugar reduction: the evidence for action. London: Public Health England; 2015.

18. HM Treasury. Budget 2016. London: HM Treasury; 2016. Available from https://www.gov.uk/government/publications/budget-2016-documents/budget-2016

19. Powell LM, Maciejewski ML. Taxes and sugar-sweetened beverages. JAMA. 2018;319(3): 229-230.

20. UK Government. Soft drink industry levy comes into effect. London: UK Government; 2018. Available from https://www.gov.uk/government/news/soft-drinks-industry-levy-comes-into-effect

21. HM Revenue and Customs. Policy paper: Soft drinks industry levy. London: HM Revenue and Customs; 2016. Available from https://www.gov.uk/government/publications/soft-drinks-industry-levy/soft-drinks-industry-levy#policy-objective

22. Arantxa-Colchero M, Salgado JC, Unar-Munguia M, Molina M, Ng S, Rivera-Dommarco JA. Changes in Prices After an Excise Tax to Sweetened Sugar Beverages Was Implemented in Mexico: Evidence from Urban Areas. PLoS One. 2015;10(12): e0144408.

23. Arantxa Colchero M, Popkin BM, Rivera JA, Ng SW. Beverage purchases from stores in Mexico under the excise tax on sugar sweetened beverages: observational study. BMJ. 2016;352: h6704.

24. Silver LD, Ng S, Ryan-Ibarra S, Taillie LS, Induni M, Miles DR, et al. Changes in prices, sales, consumer spending, and beverage consumption one year after a tax on sugar-sweetened beverages in Berkeley, California, US: A before-and-after study. PLoS Medicine. 2017;14(4): e1002283.

25. Caro JC, Corvalan C, Reyes M, Silva A, Popkin B, Taillie LS. Chile’s 2014 sugar-sweetened beverage tax and changes in prices and purchases of sugar-sweetened beverages: An observational study in an urban environment. PLoS Med. 2018;15(7): e1002597.

26. White M. Evaluation of the health impacts of the UK Treasury Soft Drinks Industry Levy (SDIL). London: National Institute of Health Research; 2018. Available from https://njl-admin.nihr.ac.uk/document/download/2010886

27. Martensen R. Corporate brand image, satisfaction and store loyalty. Int J Retail and Distribution Management. 2007;35(7): 544-555.

28. Burch D, Lawrence G. Supermarket own-brands, supply chains and the transformation of the agri-food system. Int J Sociology of Agriculture and Food. 2005;13(1): 1-18.

29. Bernal JL, Cummins S, Gasparrini A. The use of controls in interrupted time series studies of public health interventions. Int J Epidemiol. 2018;47(6): 2082-2093.

30. Kantar World Panel. Grocery market share UK. 12 weeks ending August 2019. Available from https://www.kantarworldpanel.com/en/grocery-market-share/great-britain

31. Harrington RA, Adhikari V, Rayner M, Scarborough P. Nutrient composition databases in the age of big data: foodDB, a comprehensive, real-time database infrastructure. BMJ Open. 2019;9:e026652.

32. Bernal JL, Cummins S, Gasparrini A. Interrupted time series regression for the evaluation of public health interventions: a tutorial. Int J Epidemiol. 2017;46(1): 348-355.

33. Office for National Statistics. Consumer price inflation, UK: March 2019. Newport: Office for National Statistics; 2019. Available from https://www.ons.gov.uk/economy/inflationandpriceindices/bulletins/consumerpriceinflation/march2019

34. Corless J. Shrinkflation: how many of our products are getting smaller? Newport: Office for National Statistics; 2019. Available from https://www.ons.gov.uk/economy/inflationandpriceindices/articles/theimpactofshrinkflationoncpihuk/howmanyofourproductsaregettingsmaller

35. World Cancer Research Fund. NOURISHING database. Available from https://www.wcrf.org/int/policy/nourishing-database

36. HM Government. Childhood obesity – a plan for action. Chapter 2. London: HM Government; 2018. Available from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/718903/childhood-obesity-a-plan-for-action-chapter-2.pdf

37. Public Health England. Salt reduction targets for 2017. London: Public Health England; 2017. Available from https://www.gov.uk/government/publications/salt-reduction-targets-for-2017

38. Etile F, Lecocq S, Boizot-Szanai C. The incidence of soft-drink taxes on consumer prices and welfare: evidence from the French "soda tax". Health, Econometrics and Data Group: University of York, 2018. Available from http://www.york.ac.uk/economics/postgrad/herc/hedg/wps/

39. Babyak MA. What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models. Psychosomatic Med. 2004;66(3): 411-421.

40. Breeze P, Womack R, Pryce R, Brennan A, Goyder E. The impact of a local sugar sweetened beverage health promotion and price increase on sales in public leisure centre facilities. PLOS One. 2018:13(5): p.e0194637.

41. Cornelsen L, Mytton O, Adams J, Gasparrini A, Iskander D, Knai C, et al. Change in non-alcoholic beverage sales following a 10-pence levy on sugar-sweetened beverages within a national chain of restaurants in the UK: interrupted time series analysis of a natural experiment. J Epidemiol Comm Health. 2017;71: 1107-1112.

42. Teng AM, Jones AC, Mizdrak A, Signal L, Genc M, Wilson N. Impact of sugar-sweetened beverage taxes on purchases and dietary intake: systematic review and meta-analysis. Obesity Rev. 2019: 1-18.

43. Luger M, Winzer E, Schätzer M, Dämon S, Moser N, Blagusz K, et al. Gradual reduction of free sugars in beverages on sale by implementing the beverage checklist as a public health strategy. Eur J Public Health. 2018;28(5): 961-967.

44. Eyles H, Webster J, Jebb S, Capelin C, Neal B, Ni Mhurchu C. Impact of the UK voluntary sodium reduction targets on the sodium content of processed foods from 2006 to 2011: Analysis of household consumer panel data. Prev Med. 2013;57(5): 555-560.

45. Pombo-Rodrigues S, Hashem K, He F, MacGregor G. Salt and sugars content of breakfast cereals in the UK from 1992 to 2015. Public Health Nutr. 2017;20(08): 1500-1512.

46. Knai C, Petticrew M, Douglas N, Durand MA, Eastmure E, Nolte E, et al. The Public Health Responsibility Deal: using a systems-level analysis to understand the lack of impact on alcohol, food, physical activity, and workplace health sub-systems. Int J Env Res and Public Health. 2018;15(12): 2895.

47. Public Health England. Sugar reduction: Report on progress between 2015 and 2018. London: Public Health England; 2019. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/832182/Sugar_reduction__Yr2_progress_report.pdf

48. Bandy L, Scarborough P, Harrington RA, Rayner M, Jebb SA. Reductions in sugar sales from soft drinks in the UK from 2015-2018. BMC Medicine, 2019 (in press).

49. Alvarez-Sanchez C, Contento I, Jimenez-Aguilar A, Koch P, Gray HL, Guerra LA, et al. Does the Mexican sugar-sweetened beverage tax have a signalling effect? ENSANUT 2016. PLoS One. 2018;13(8): e0199337.

Supporting material

S1 Appendix Analysis of impact of soft drinks industry levy on proportion of drinks over higher levy threshold (8g sugar per 100ml)

S2 Appendix Model parameters for all models presented in the main analysis and supplementary material

S3 Appendix Comparison of foodDB and BrandView datasets

S4 Appendix Pre-published protocol

S5 Appendix Analysis of impact of soft drinks industry levy on mean sugar levels

The impact of the announcement and implementation of the UK Soft Drinks Industry Levy on sugar content, price, product size and number of available soft drinks in the UK, 2015-19: a controlled interrupted time series analysis

Supplementary material

Contents

S1 Appendix: Comparison of foodDB and BrandView datasets

Introduction: This appendix provides a comparison of the two datasets that have been combined for analysis of the impact of the announcement and implementation of the Soft Drinks Industry Levy (SDIL) on the proportion of drinks over each levy threshold (see main paper and appendix 3) and on the mean sugar levels in drinks (see appendix 2).

Methods: We used data collected from the websites of the three leading UK supermarkets (Asda, Sainsbury's and Tesco) that together account for 58% of UK grocery sales[1]. One source was a web-scraping and data processing software platform called foodDB which was developed in-house by researchers in the Centre on Population Approaches for Non-Communicable Disease Prevention at the University of Oxford. Full details of the methods of data collection using foodDB are provided elsewhere[2]. Briefly, foodDB collects data on over 99% of all food and drink products available for purchase on the supermarket websites each week, including product name, nutritional information, ingredients, product size, price and whether or not the product is on promotion.

To assess validity of the data collected by foodDB, a validation exercise was conducted that compared foodDB data with equivalent data collected from 295 randomly selected products in real life stores. Agreement between foodDB and the store sample for both sugar levels (g per 100g / 100ml) and price (£ per 100g / 100ml) was measured by assessing percentage agreement between the two sources and observing Bland-Altman plots for detection of bias. For percentage agreement, we rounded sugar levels to the nearest gram per 100g / 100ml, as this data was not always recorded to the same number of decimal places in each dataset.

For the controlled interrupted time series analyses, we used weekly data from foodDB from 26th November 2017 (its initial data collection period) until 17th February 2019, consisting of 58 time points (NB: 6 weeks of data collection were excluded from the dataset, due to errors with the data collection which resulted in collection of data on less than 90% of all observed drinks).

The second data source was the commercial company BrandView, which extracts data from products available in Asda, Sainsbury's and Tesco. We purchased data corresponding to the first of every month between August 2015 and September 2018. The initial data point was dropped as data was available for less than 90% of all observed drinks, leaving 37 time points.

Both the foodDB and BrandView datasets were restricted to our definition of soft drinks (see main paper), and then categorised as intervention or control based on supermarket categorisation and manual inspection of product names, using similar code and methods for each dataset. We categorised drinks as 'own-brand' if the product name contained Asda, Tesco or Sainsbury's, and as 'branded' otherwise.

To compare data collected from these two sources we compared drink categories, supermarkets, branded status, intervention / control status, price, product size and sugar level with Chi squared tests for categorical variables and Wilcoxon rank-sum tests for continuous variables. We observed trends in own-brand and branded products separately across the entire data collection period

[1] Kantar World Panel. Grocery market share UK. 12 weeks ending September 2018. Available at https://www.kantarworldpanel.com/en/grocery-market-share/great-britain Accessed 24th April 2019.
[2] Harrington RA, Adhikari V, Rayner M, Scarborough P. Nutrient composition databases in the age of big data: foodDB, a comprehensive, real-time database infrastructure. *BMJ Open*, 2019 (in press).

(including November 2017 – September 2018 where data were available from both sources). We plotted trends in the following variables: Number of products per data snapshot; mean sugar levels (g per 100ml); geometric mean price (p per 100ml); and geometric mean product size (ml). NB: geometric means were used for comparability with the main analyses, where these variables were log-transformed for the regression models.

Results: Of the 295 products identified in real-life stores and compared with equivalent products collected using foodDB, 193 had data for sugar levels in both datasets and 254 had data for price in both datasets. For sugar, 90.0% (95% confidence intervals 85.3%-93.9%) had the same sugar levels. For price, 77.6% (72.4%-82.7%) of the products matched between the online and real-life stores.

The Bland-Altman plots are shown in Figs A and B and demonstrate no evidence of systematic difference between the two data sources.

Fig A Bland-Altman plot comparing price (p per 100g / 100ml) of 254 products identified in real-life stores and online

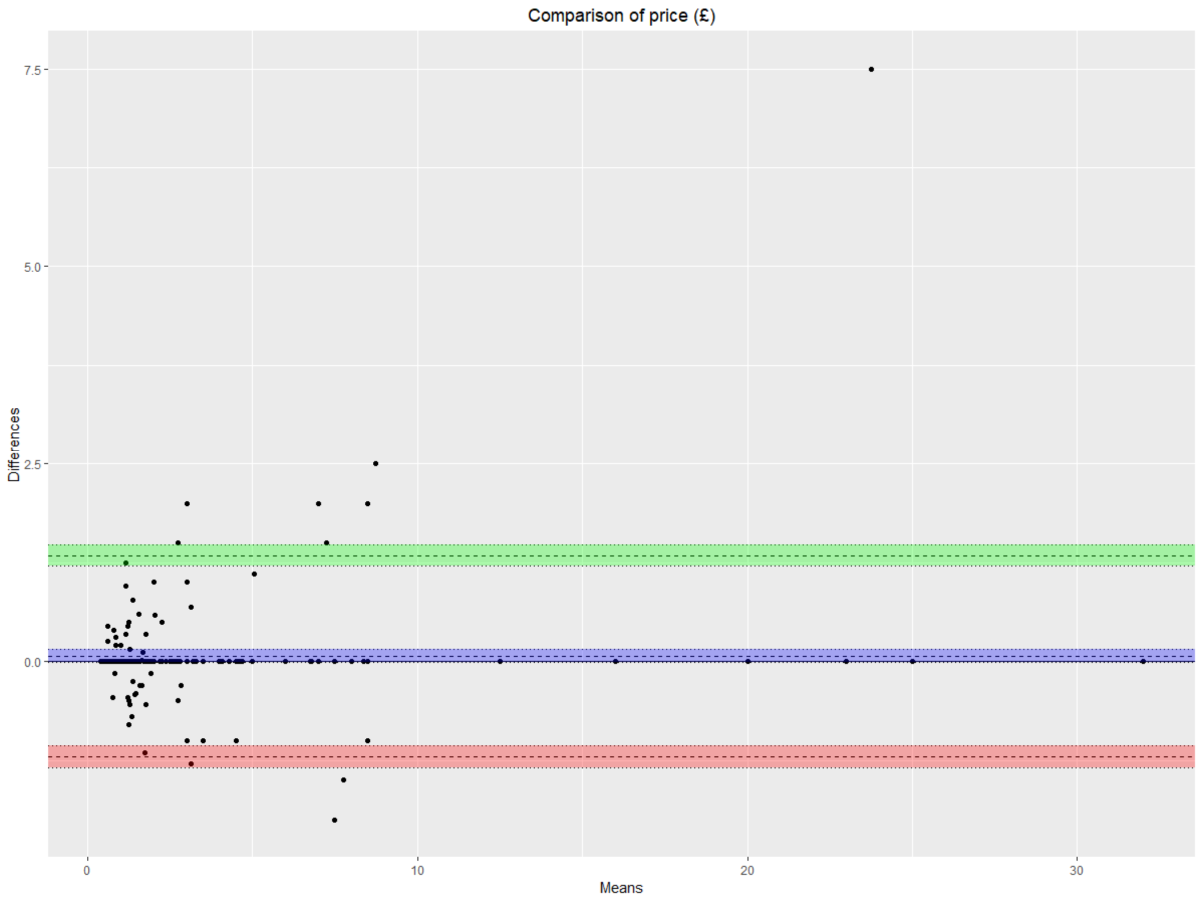


Fig B Bland-Altman plot comparing sugar (g per 100g / 100ml) of 193 products identified in real-life stores and online

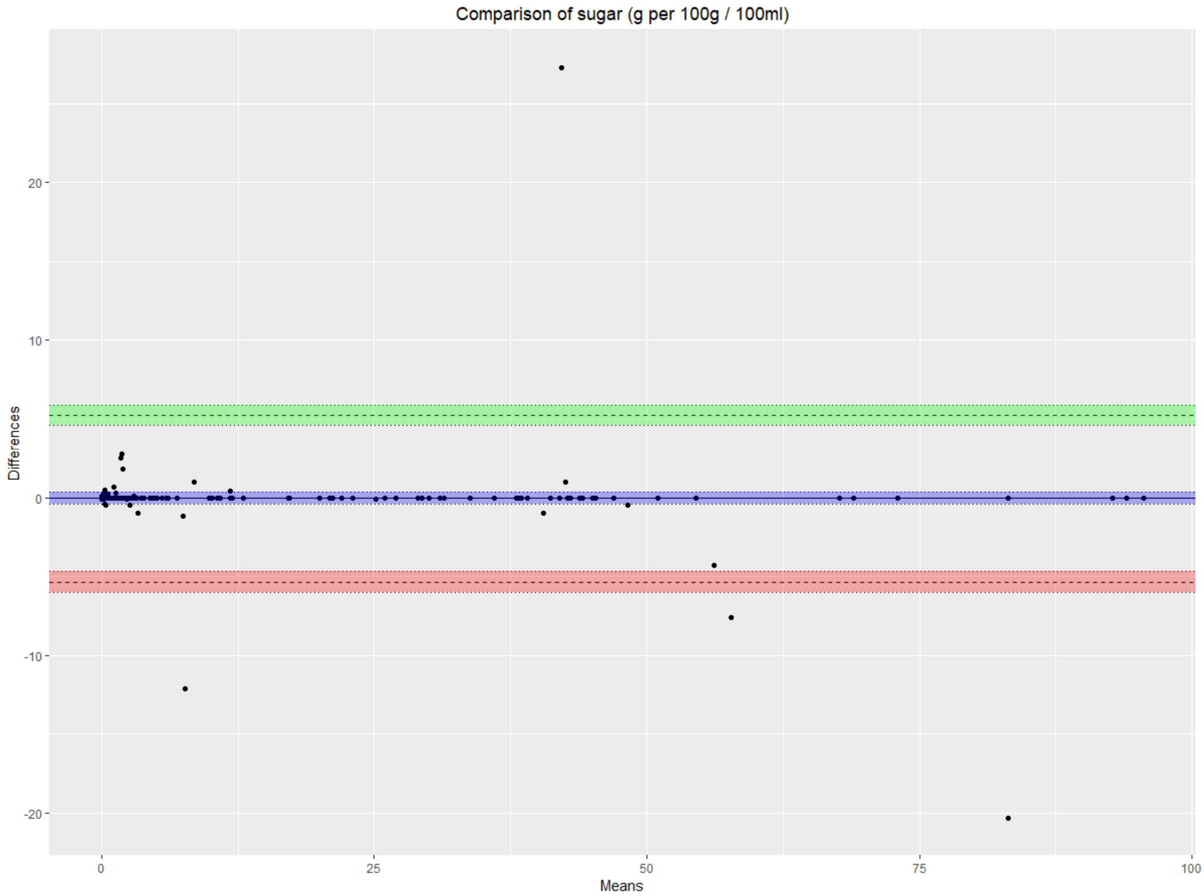


Table A shows descriptive statistics for the two datasets. There were differences between the two datasets in both the types of drinks observed and the amount of observations from each supermarket, with the foodDB dataset collecting data on similar number of drinks from each of the three supermarkets whereas BrandView predominantly provided data from Tesco. Splits between branded and own-brand status, and between intervention and control drinks were similar across the two datasets, but a greater proportion of branded products and control drinks were found in foodDB. There were small differences in the median price and sugar levels of drinks collected in the two datasets, which may reflect the different time periods over which data were collected.

Table A Descriptive statistics comparing the foodDB and BrandView datasets

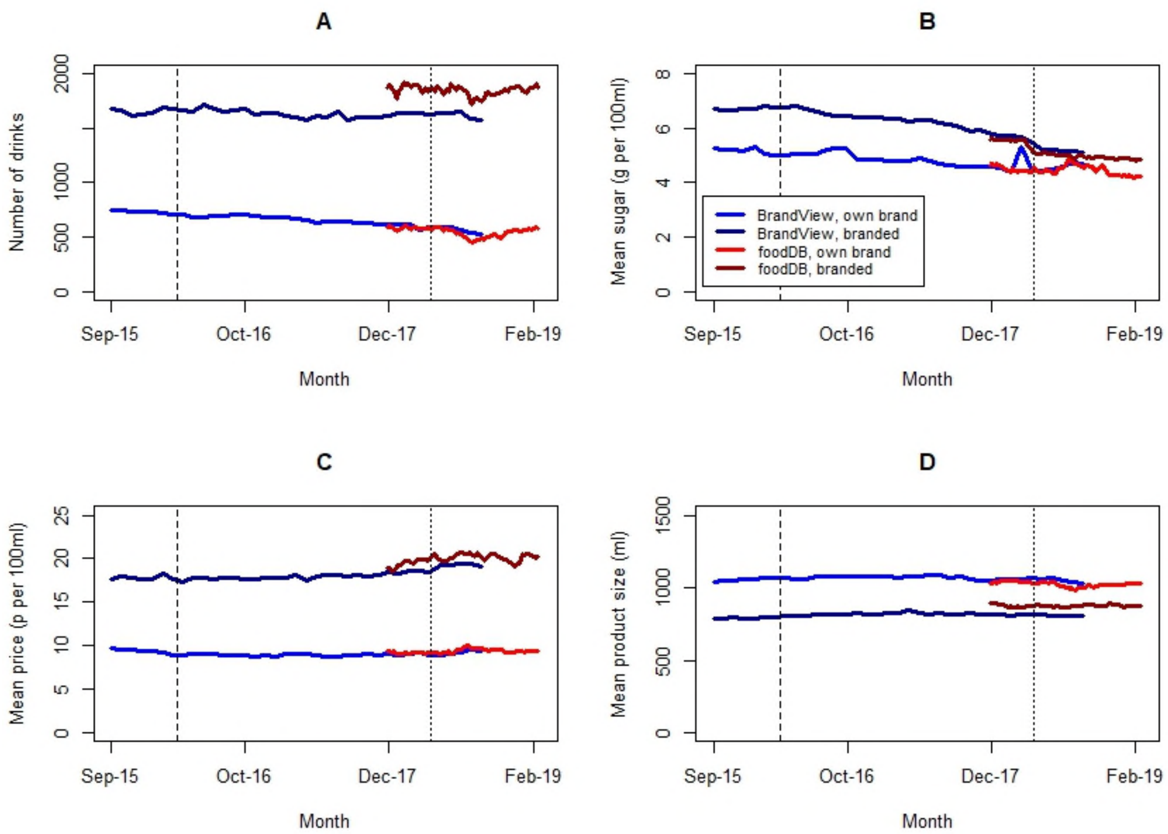
Variable	*foodDB*	*BrandView*	p^1
Type of drink, n (%)			
Carbonate	44,230 (30.7)	33,323 (37.6)	
Energy drink	13,832 (9.6)	3,434 (3.9)	
Squash or cordial	12,061 (8.4)	7,887 (8.9)	
Flavoured water	8,539 (5.9)	4,125 (4.7)	
Milk-based drink	20,157 (14.0)	9,480 (10.7)	
Fruit juice and smoothies	45,253 (31.4)	30,373 (34.3)	<0.001
Supermarket, n (%)			
Tesco	47,632 (33.0)	51,254 (57.8)	
Sainsbury's	50,069 (34.8)	15,963 (18.0)	
Asda	46,371 (32.2)	21,405 (24.2)	<0.001
Branded status, n (%)			
Branded	110,924 (77.0)	63,460 (71.6)	
Own-brand	33,148 (23.0)	25,162 (28.4)	<0.001
SDIL status, n (%)			
Intervention	89,175 (61.9)	59,703 (67.4)	
Control	54,897 (38.1)	28,919 (32.6)	<0.001
Price £ per 100ml, median (IQR)	0.17 (0.10-0.27)	0.15 (0.10-0.25)	<0.001
Product size ml, median (IQR)	1000 (604-1500)	1000 (500-1500)	0.504
Sugar g per 100ml, median (IQR)	4.6 (0.5-8.6)	5.1 (0.5-10.0)	<0.001

[1] *p values are derived from Chi-squared tests for categorical variables and Wilcoxon rank-sum tests for continuous variables*

Fig C shows overlapping trends in key variables between the two datasets. For mean sugar levels, price and product size there is strong agreement between the two datasets for own-brand products. However, for branded products there is less agreement. Mean product size and price were higher in branded foods (by 65ml and 0.99p per 100ml, respectively) in the foodDB dataset than in the BrandView dataset, and mean sugar levels were lower by 0.16g per 100ml.

Both the foodDB and BrandView datasets collected similar number of own-brand products at each data collection snapshot, but foodDB collected on average 225 more branded drinks per snapshot.

Fig C Comparison of trend data in BrandView (Sep 15 – Sep 18) and foodDB (Nov 17 – Feb 19) for branded and own-brand products separately for A: number of drinks per snapshot, B: mean sugar level (g per 100ml), C: mean price (p per 100ml), D: mean product size (ml)



S2 Appendix: Analysis of impact of soft drinks industry levy on mean sugar levels

Introduction: This appendix reports results of a pre-determined analysis (see pre-published protocol https://njl-admin.nihr.ac.uk/document/download/2010886) of the impact of the announcement and implementation of the SDIL on mean sugar levels of intervention and control soft drinks in the UK.

Methods: We used the same dataset that was used for our analysis of the impact of the SDIL on the proportion of soft drinks above the levy sugar threshold, with the same definitions of intervention and control drinks. The main analysis is restricted to intervention drinks, with a second analysis using the same regression model but restricted to control drinks. Mean sugar levels over time were compared with a counterfactual which extrapolates trends from the period before the announcement of the SDIL. Full details of the datasets used, including definitions of key terms, can be found in the main manuscript.

The outcome variable for this analysis (sugar level of soft drinks) was not normally distributed in the dataset, nor did it follow a distribution that could be transformed to normality. Therefore, linear regression using the continuous variable was not appropriate. Instead, we collapsed the dataset into mean sugar levels (g per 100ml) for intervention and control drinks in the 85 time points between September 2015 and February 2019 available in the dataset. Linear regression models were then run against these collapsed data points.

Initial observation of the man sugar levels over time suggested non-linear trends between the announcement and implementation of the SDIL. Therefore, models were built allowing for polynomial trends during this period, with the final model selected on the basis of likelihood ratio tests comparing nested models using a threshold of $p = 0.05$ to decide whether adding extra polynomial order improved model fit sufficiently. This resulted in a cubic polynomial model fit between these points.

Although the continuous outcome variable used in the linear regression models (mean sugar levels) was not normally distributed, inspection of model residuals did not reveal any evidence of heteroscedasticity or deviation from normality.

We observed the distribution of sugar levels in drinks prior to the announcement of the SDIL and after its implementation to explore how manufacturers had reformulated their products.

Results: Fig D shows the trend in mean sugar levels of both intervention and control drinks over time. For intervention drinks, sugar levels were falling slowly before the announcement of the SDIL ($p = 0.020$), but accelerated after the announcement ($p < 0.001$), culminating in a substantial reduction in sugar levels just before the implementation of the SDIL ($p < 0.001$). After the implementation, the trend in sugar levels returned to a level that was not different to pre-announcement trends ($p = 0.666$). By February 2019, mean sugar levels in intervention soft drinks were lower than the counterfactual scenario of no SDIL by 2.13g per 100ml (95% CI: 2.08, 2.18). The control analysis found no evidence of difference in trends due to either the announcement or the implementation of the SDIL.

Fig D Mean sugar levels (g per 100ml) for eligible and exempt drinks, September 2015 – February 2019

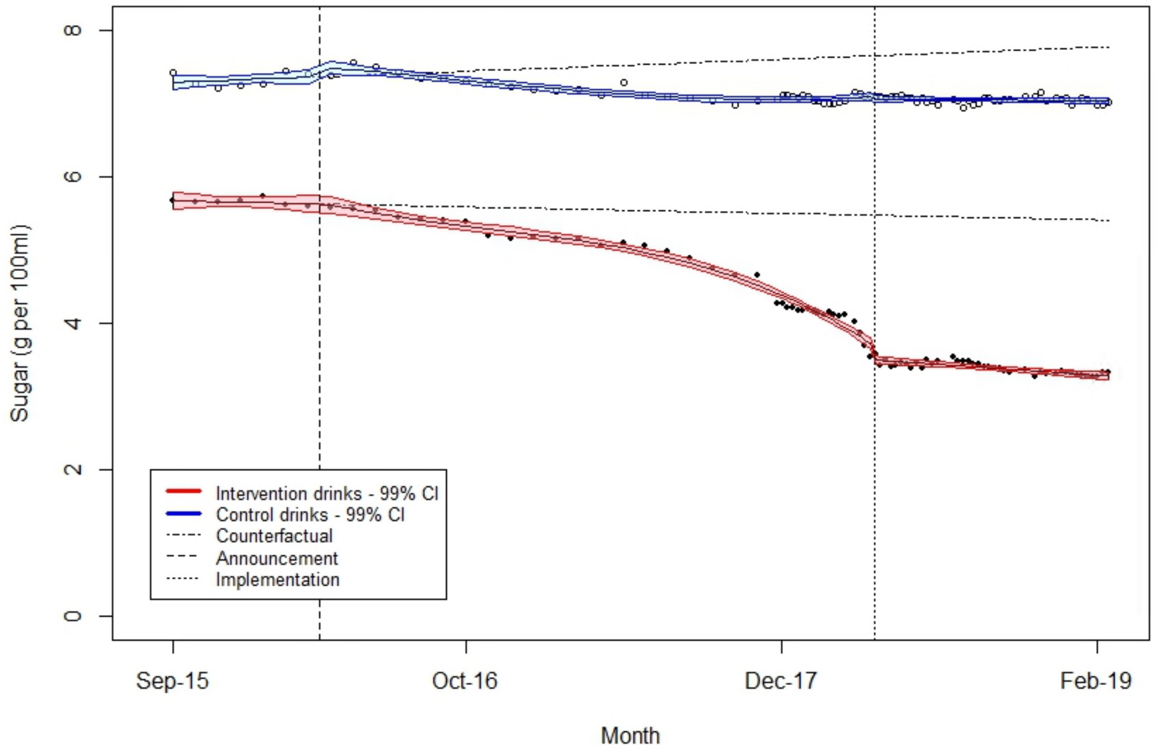
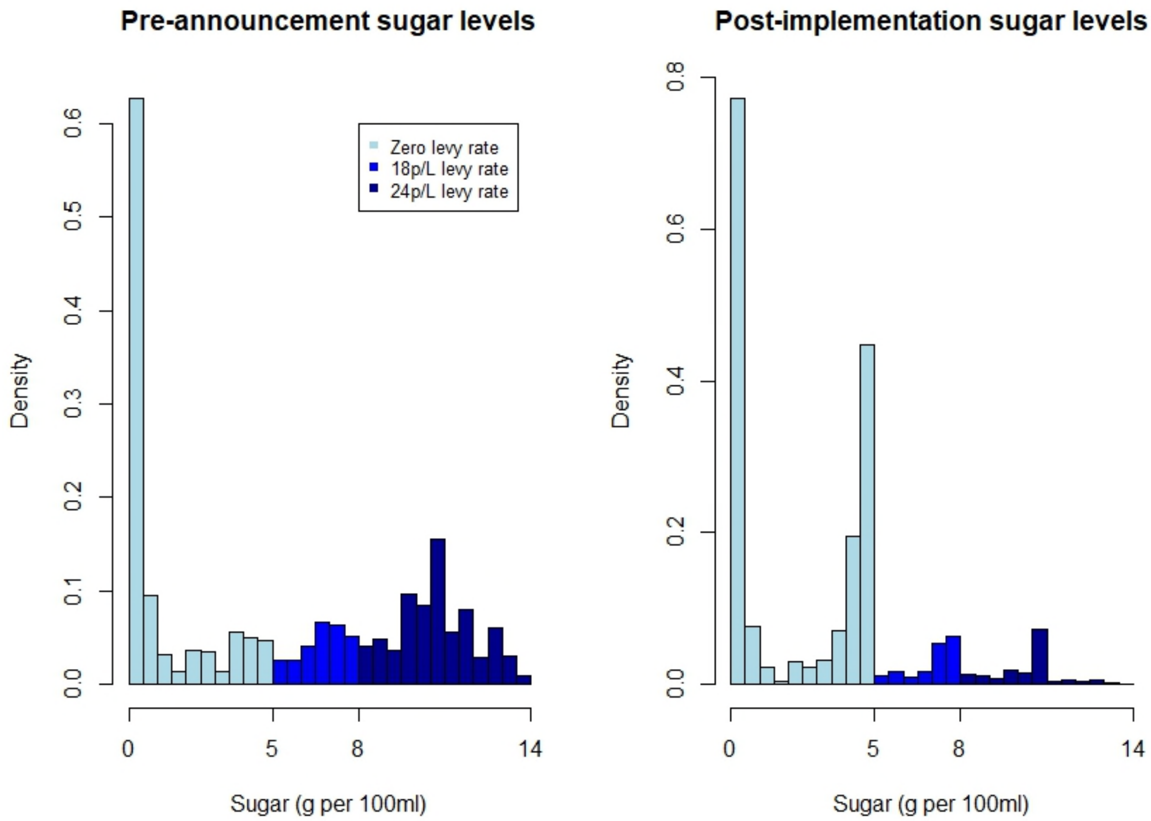


Fig E shows histograms of the sugar levels in observations of drinks before the announcement of the SDIL and after its introduction. Prior to the announcement of the SDIL, there is a large spike of drinks with less than 1g sugar per 100ml, but sugar levels in drinks are fairly even elsewhere. After the implementation of the SDIL, there is another large spike in drinks with sugar levels between 4.5g and 5.0g sugar per 100ml, suggesting that manufacturers reacted to the levy by removing just enough sugar from drinks to avoid the levy.

Fig E Sugar levels (g per 100ml) in observations of drinks prior to the announcement of the SDIL and post-implementation of the SDIL



S3 Appendix: Analysis of impact of soft drinks industry levy on proportion of drinks over higher levy threshold (8g sugar per 100ml)

Introduction: The main paper reports results of models that measure the impact of the announcement and the implementation of the SDIL on the proportion of intervention and control drinks that are over the levy sugar threshold (5g sugar per 100ml). This appendix reports equivalent results for models that measure the impact of the SDIL on the proportion of drinks over the high levy threshold (8g sugar per 100ml).

Methods: The datasets used, definitions of key terms and descriptions of regression models used are reported in the main paper. The only difference is the threshold used for the binary variable in the logistic regression models – here the outcome variable is 1 if a drink contains greater than 8g sugar per 100ml and 0 otherwise. Additionally, we show trends in the raw data for both intervention and control drinks over both levy thresholds using stacked line charts.

Results: Table B compares the percentage of drinks over the high levy threshold with a counterfactual where the SDIL was not announced or implemented and Fig F shows the results for all intervention and control drinks. The percentage of intervention drinks over the high levy threshold reduced after the announcement of the SDIL only slowly at first, but with rapid changes just prior to the implementation. Just 50 days before the implementation, intervention drinks with enough sugar to be levied at the high rate had fallen by 20.0 (95% CI: 19.5, 20.5) percentage points – 50 days after implementation drinks levied at this rate had fallen by 28.7 (28.3, 29.0) percentage points. As of February 2019, there was a 31.3 (30.9, 31.6) percentage point fall, leaving only 7.1% (6.7%, 7.5%) of intervention drinks above the high levy threshold. Equivalent models for the control drinks found no impact of the announcement or implementation of the SDIL on percentage of drinks above the high levy threshold (p > 0.05 for all regression parameters). Due to a (non-significant) upwards trend in the percentage of control drinks above the high levy threshold before the announcement, the comparison with the counterfactual shows considerable falls (see Fig F). The pattern of sugar reduction in own-brand and branded drinks was very different – for own-brand drinks, sugar levels were already falling before the announcement of the SDIL, but these falls accelerated after the announcement. However, by the time of the implementation of the SDIL, only 3.5% (3.1%, 4.0%) of own-brand eligible drinks remained over the high levy threshold and further sugar reduction stalled. For branded drinks, there was a large fall in the proportion of drinks either side of the implementation of the levy, which had resulted in a 40.4 (40.0, 40.9) percentage point fall in the number of branded eligible drinks over the high levy threshold by February 2019.

Table B: Difference between observed and counterfactual (extrapolation of pre-announcement trends) percentage of drinks over the high levy sugar threshold (>8g sugar per 100ml)

	Difference in percentage[1] of drinks over levy sugar threshold (95% confidence intervals)			
	5th May 2016 (50 days post-announcement)	15th February 2018 (50 days pre-implementation)	26th May 2018 (50 days post-implementation)	17th February 2019 (End of dataset)
All intervention drinks	-0.0 (-1.6, 0.7)	-20.0 (-20.5, -19.5)	-28.7 (-29.0, -28.3)	-31.3 (-31.6, -30.9)
Branded intervention drinks	-1.3 (-2.7, -0.0)	-24.7 (-25.3, -24.1)	-36.1 (-36.5, -35.7)	-40.4 (-40.9, -40.0)
Own-brand intervention drinks	1.8 (-0.1, 3.8)	-9.6 (-10.1, -8.9)	-9.8 (-10.3, -9.3)	-7.7 (-8.2, -7.0)
All control drinks	1.3 (-0.4, -3.0)	-11.9 (-12.7, -11.1)	-13.5 (-14.2, -12.7)	-15.6 (-16.5, -14.6)

[1] Results are presented as percentage point differences compared to the counterfactual (extrapolation of pre-announcement trend).

Fig F: Change in proportion of drinks over the high levy threshold (8g sugar per 100ml), September 2015 to February 2019, intervention and control drinks, compared to counterfactual scenario of no SDIL

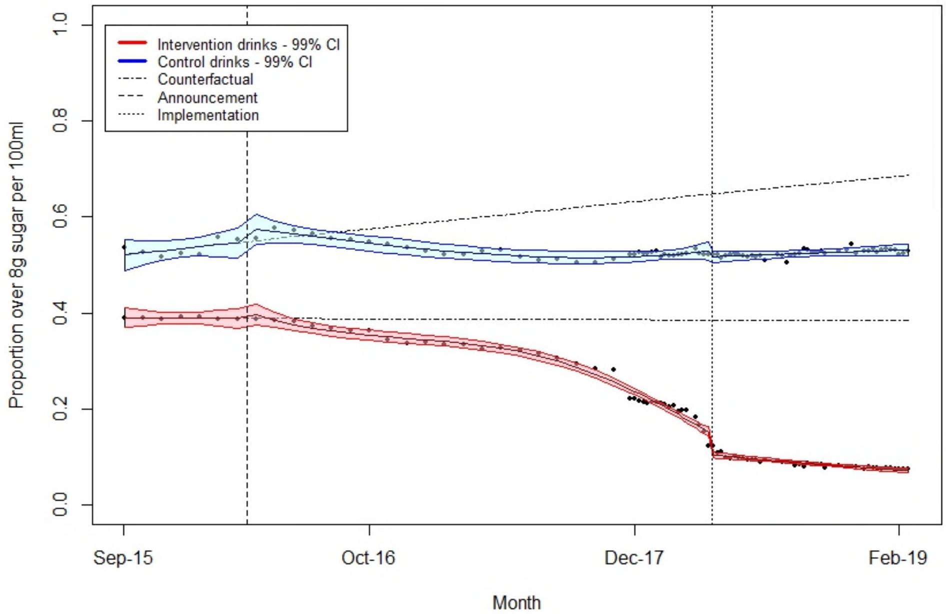
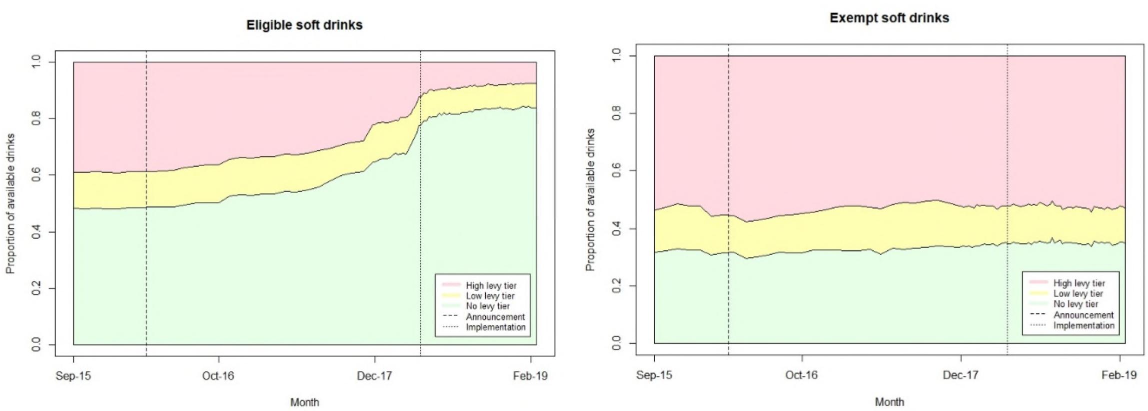


Fig G shows the proportion of both intervention and control drinks over each levy threshold and shows how the pace of reformulation of intervention drinks increased between the announcement and implementation of the SDIL.

Fig G Trends in the proportion of intervention (eligible) and control (exempt) drinks over each levy threshold



S4 Appendix: Model parameters for all models presented in the main analysis and supplementary material

Parameter description:

T	Time, measured in 100 day units, with T = 0 at the point of the implementation of the SDIL (6th April 2018)
A	Dummy variable indicating the time between the announcement (16th March 2016) and implementation (6th April 2018) of the UK soft drinks industry levy (SDIL) – **This parameter estimates the level change due to announcement of the SDIL**
AT	Interaction between A and T
ATT	Interaction between A and T^2
ATTT	Interaction between A and T^3 – **These parameters estimate the slope change due to the announcement of the SDIL**
I	Dummy variable indicating the time after the implementation of the SDIL – **This parameter estimates the level change due to the implementation of the SDIL**
IT	Interaction between I and T – **This parameter estimates the slope change due to the implementation of the SDIL**
Dec	A dummy variable indicating the month of December

Table C: Model parameters for all models reported in main paper

Parameter	*Effect size*	*95% confidence intervals*	*p*
			Above levy sugar threshold, intervention drinks
(Intercept)	-0.005	(-0.504, 0.495)	0.985
T	-0.009	(-0.067, 0.049)	0.77
A	-1.036	(-1.538, -0.533)	<0.001
AT	-0.462	(-0.554, -0.370)	<0.001
ATT	-0.083	(-0.106, -0.059)	<0.001
ATTT	-0.005	(-0.008, -0.003)	<0.001
I	-1.394	(-1.895, -0.893)	<0.001
IT	-0.089	(-0.150, -0.027)	0.005
			Above levy sugar thresholds, control drinks
(Intercept)	0.932	(0.117, 1.747)	0.025
T	0.020	(-0.074, 0.115)	0.673
A	-0.304	(-1.121, 0.513)	0.465
AT	-0.070	(-0.206, 0.065)	0.309
ATT	-0.009	(-0.041, 0.024)	0.612
ATTT	-0.001	(-0.004, 0.002)	0.629
I	-0.312	(-1.127, 0.504)	0.454
IT	-0.020	(-0.117, 0.078)	0.694
			Price, all drinks, high levy category, intervention
(Intercept)	3.243	(3.224, 3.262)	<0.001

Parameter	*Effect size*	*95% confidence intervals*	*p*
T	0.021	(0.010, 0.031)	<0.001
I	0.029	(-0.002, 0.059)	0.064
Dec	-0.024	(-0.049, 0.002)	0.068
Price, all drinks, low levy category, intervention			
(Intercept)	3.493	(3.474, 3.512)	<0.001
T	0.019	(0.009, 0.028)	<0.001
I	-0.033	(-0.063, -0.003)	0.031
Dec	-0.064	(-0.089, -0.039)	<0.001
Price, all drinks, no levy category, intervention			
(Intercept)	2.630	(2.621, 2.639)	<0.001
T	0.022	(0.017, 0.027)	<0.001
I	0.025	(0.011, 0.040)	<0.001
Dec	-0.036	(-0.049, -0.024)	<0.001
Price, all drinks, control			
(Intercept)	3.128	(3.120, 3.137)	<0.001
T	0.006	(0.002, 0.011)	0.006
I	-0.006	(-0.020, 0.007)	0.357
Dec	0.002	(-0.009, 0.014)	0.693
Price, branded drinks, high levy category, intervention			
(Intercept)	3.241	(3.221, 3.260)	<0.001
T	0.021	(0.010, 0.031)	<0.001
I	0.045	(0.013, 0.076)	0.005
Dec	-0.023	(-0.049, 0.004)	0.09
Price, branded drinks, low levy category, intervention			
(Intercept)	3.549	(3.531, 3.566)	<0.001
T	0.022	(0.012, 0.031)	<0.001
I	-0.051	(-0.079, -0.023)	<0.001
Dec	-0.068	(-0.091, -0.045)	<0.001
Price, branded drinks, no levy category, intervention			
(Intercept)	2.810	(2.801, 2.819)	<0.001
T	0.014	(0.009, 0.019)	<0.001
I	0.015	(0.001, 0.030)	0.040
Dec	-0.038	(-0.05, -0.026)	<0.001
Price, branded drinks, control			
(Intercept)	3.297	(3.288, 3.306)	<0.001
T	0.007	(0.002, 0.012)	0.004
I	-0.015	(-0.029, -0.001)	0.036
Dec	0.004	(-0.008, 0.015)	0.539
Price, own-brand drinks, high levy category, intervention			
(Intercept)	3.311	(3.228, 3.393)	<0.001
T	0.016	(-0.017, 0.049)	0.336
I	-0.256	(-0.368, -0.144)	<0.001
Dec	-0.032	(-0.124, 0.059)	0.490
Price, own-brand drinks, low levy category, intervention			
(Intercept)	2.496	(2.403, 2.590)	<0.001
T	-0.017	(-0.061, 0.026)	0.433
I	0.451	(0.312, 0.590)	<0.001
Dec	0.013	(-0.102, 0.129)	0.822

Parameter	*Effect size*	*95% confidence intervals*	*p*
Price, own-brand drinks, no levy category, intervention			
(Intercept)	1.976	(1.958, 1.994)	<0.001
T	0.028	(0.018, 0.038)	<0.001
I	-0.011	(-0.040, 0.019)	0.467
Dec	-0.001	(-0.025, 0.022)	0.909
Price, own-brand drinks, control			
(Intercept)	2.508	(2.495, 2.520)	<0.001
T	0.002	(-0.005, 0.009)	0.556
I	0.001	(-0.019, 0.021)	0.920
Dec	0.005	(-0.012, 0.022)	0.570
Product size, all drinks, high levy category, intervention			
(Intercept)	6.629	(6.603, 6.656)	<0.001
T	-0.048	(-0.063, -0.033)	<0.001
I	0.001	(-0.043, 0.046)	0.960
Product size, all drinks, low levy category, intervention			
(Intercept)	6.455	(6.436, 6.474)	<0.001
T	0.010	(0.000, 0.021)	0.059
I	0.020	(-0.011, 0.051)	0.210
Product size, all drinks, no levy category, intervention			
(Intercept)	6.922	(6.914, 6.931)	<0.001
T	-0.011	(-0.016, -0.006)	<0.001
I	-0.002	(-0.017, 0.013)	0.783
Product size, all drinks, control			
(Intercept)	6.580	(6.572, 6.587)	<0.001
T	-0.003	(-0.007, 0.001)	0.132
I	0.006	(-0.006, 0.018)	0.321
Product size, branded drinks, high levy category, intervention			
(Intercept)	6.635	(6.608, 6.663)	<0.001
T	-0.048	(-0.063, -0.032)	<0.001
I	-0.009	(-0.055, 0.038)	0.711
Product size, branded drinks, low levy category, intervention			
(Intercept)	6.432	(6.413, 6.451)	<0.001
T	0.008	(-0.003, 0.019)	0.151
I	0.026	(-0.006, 0.058)	0.116
Product size, branded drinks, no levy category, intervention			
(Intercept)	6.890	(6.880, 6.900)	<0.001
T	-0.008	(-0.014, -0.002)	0.009
I	0.000	(-0.018, 0.018)	0.997
Product size, branded drinks, control			
(Intercept)	6.513	(6.505, 6.522)	<0.001
T	-0.003	(-0.008, 0.002)	0.281
I	0.009	(-0.005, 0.023)	0.207
Product size, own-brand drinks, high levy category, intervention			
(Intercept)	6.443	(6.357, 6.529)	<0.001
T	-0.058	(-0.093, -0.023)	0.001
I	0.249	(0.129, 0.368)	<0.001
Product size, own-brand drinks, low levy category, intervention			
(Intercept)	6.864	(6.815, 6.912)	<0.001

Parameter	*Effect size*	*95% confidence intervals*	*p*
T	0.034	(0.010, 0.058)	0.006
I	-0.157	(-0.232, -0.082)	<0.001
Product size, own-brand drinks, no levy category, intervention			
(Intercept)	7.038	(7.025, 7.051)	<0.001
T	-0.020	(-0.028, -0.012)	<0.001
I	0.005	(-0.018, 0.028)	0.661
Product size, own-brand drinks, control			
(Intercept)	6.836	(6.827, 6.846)	<0.001
T	-0.006	(-0.012, -0.001)	0.029
I	0.008	(-0.008, 0.024)	0.351
Number of products, all drinks, high levy category, intervention			
(Intercept)	279.9	(261.5, 298.2)	<0.001
T	-49.9	(-73.4, -26.4)	<0.001
I	-26.6	(-48.3, -5.0)	0.019
IT	46.6	(22.3, 70.9)	<0.001
Number of products, all drinks, low levy category, intervention			
(Intercept)	299.5	(289.0, 310.0)	<0.001
T	-7.5	(-13.9, -1.1)	0.025
I	-1.2	(-19.7, 17.2)	0.895
Number of products, all drinks, no levy category, intervention			
(Intercept)	2234.7	(2161.0, 2308.4)	<0.001
T	30.9	(-14.1, 75.9)	0.184
I	-54.3	(-183.7, 75.2)	0.415
Number of products, all drinks, control			
(Intercept)	2023.4	(1920.4, 2126.4)	<0.001
T	93.5	(-38.5, 225.5)	0.170
I	-49.5	(-171.1, 72.1)	0.428
IT	-123.0	(-259.6, 13.5)	0.083
Number of products, branded drinks, high levy category, intervention			
(Intercept)	264.9	(248.1, 281.7)	<0.001
T	-34.9	(-56.4, -13.4)	0.002
I	-25.5	(-45.3, -5.6)	0.014
IT	31.9	(9.7, 54.2)	0.007
Number of products, branded drinks, low levy category, intervention			
(Intercept)	272.0	(262.6, 281.4)	<0.001
T	-7.1	(-12.9, -1.4)	0.018
I	1.7	(-14.8, 18.2)	0.843
Number of products, branded drinks, no levy category, intervention			
(Intercept)	1811.6	(1754.3, 1868.8)	<0.001
T	32.3	(-2.6, 67.2)	0.075
I	-12.6	(-113.2, 87.9)	0.806
Number of products, branded drinks, control			
(Intercept)	1606.6	(1524.1, 1689.0)	<0.001
T	86.3	(-19.3, 191.9)	0.114
I	-34.7	(-132, 62.6)	0.487
IT	-112.4	(-221.7, -3.1)	0.048
Number of products, own-brand drinks, high levy category, intervention			
(Intercept)	15.0	(12.9, 17.1)	<0.001

Parameter	*Effect size*	*95% confidence intervals*	*p*
T	-15.0	(-17.7, -12.3)	<0.001
I	-1.2	(-3.7, 1.3)	0.352
IT	14.7	(11.9, 17.5)	<0.001
Number of products, own-brand drinks, low levy category, intervention			
(Intercept)	24.2	(21.2, 27.2)	<0.001
T	-5.2	(-9.1, -1.4)	0.01
I	-0.2	(-3.7, 3.4)	0.927
IT	5.2	(1.2, 9.2)	0.014
Number of products, own-brand drinks, no levy category, intervention			
(Intercept)	423.1	(402.9, 443.2)	<0.001
T	-1.4	(-13.7, 10.9)	0.821
I	-41.6	(-77.0, -6.3)	0.024
Number of products, own-brand drinks, control			
(Intercept)	416.8	(392.6, 441.0)	<0.001
T	7.2	(-23.8, 38.2)	0.652
I	-14.8	(-43.3, 13.8)	0.315
IT	-10.7	(-42.8, 21.4)	0.517

S5 Pre-published protocol

The protocol for the full evaluation of the SDIL is available online here: https://njl-admin.nihr.ac.uk/document/download/2010886

The section relevant to the analyses reported in this paper is reproduced here.

Study 1a: the impact of the SDIL on non-alcoholic drinks market diversity, total sugar content and price

Study design
Using an in-house dataset collected from major UK supermarket websites, we will use interrupted time series (ITS) methods to study whether the implementation of the SDIL was associated with changes in level or trend of non-alcoholic drink market diversity, sugar content and price.

Data source
We will use an in-house, bespoke dataset (developed during our formative work) to assess non-alcoholic drink market diversification, formulation and price. We have developed automated data collection techniques (i.e. 'data scraping') and will use these to collect monthly, time-stamped data on all soft drinks available for purchase from six online UK supermarkets (Tesco, Morrison's, Asda, Sainsbury's, Waitrose and Ocado). Together these supermarkets (online and in-store) represent more than 75% of the UK grocery market.[43] The resultant database (FoodDB) contains data on the complete product range of soft drinks from each supermarket in each month.

We will add data from any new online supermarkets that open during the project. Maintenance of FoodDB will be conducted monthly to ensure that the source code that supplies the dataset continues to run appropriately (it also will be necessary to adapt this source code when online supermarkets change their appearance, format or layout).

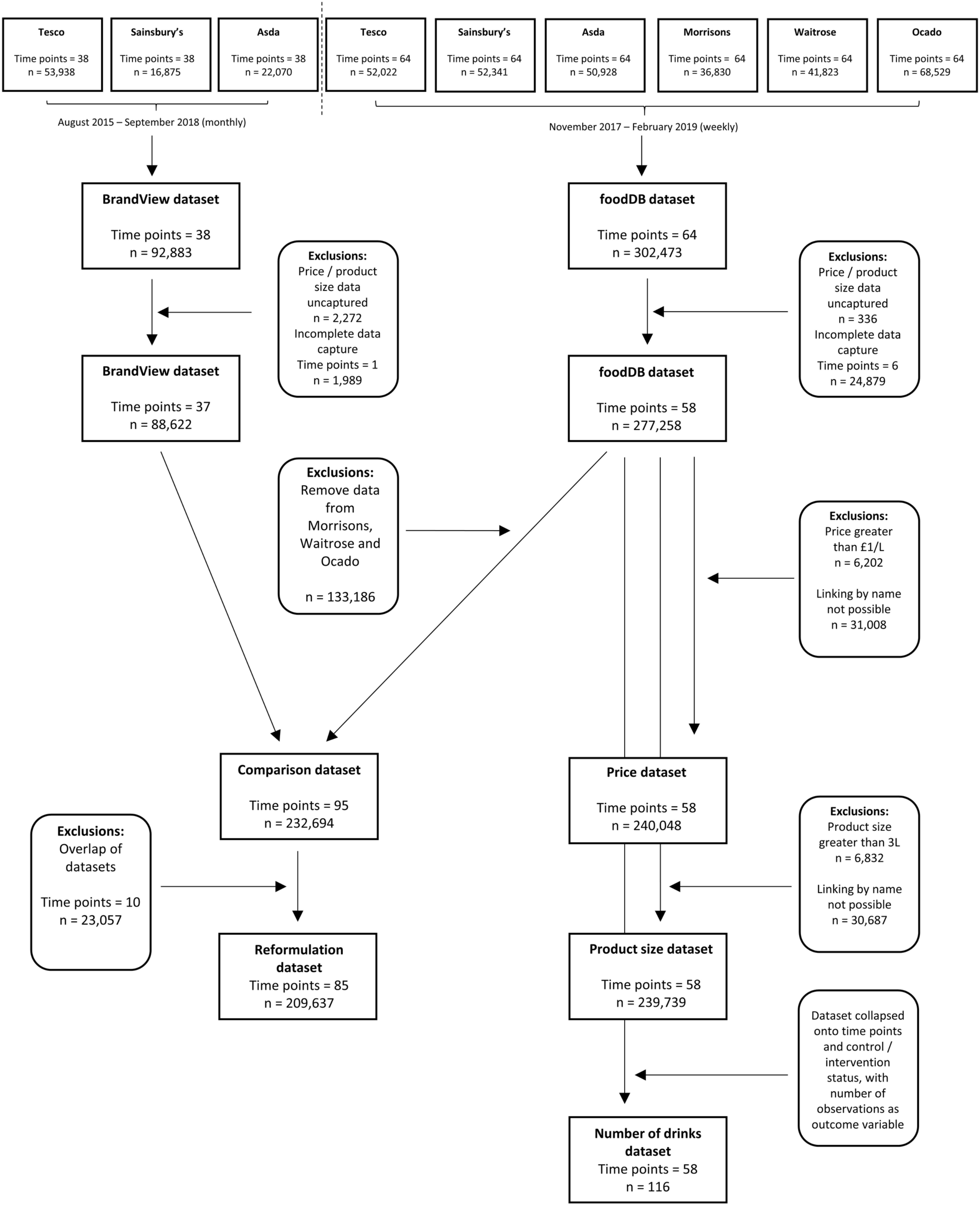
For each drink we will continue to collect: date of data collection; nutritional content; price; pack size; serving size; whether or not the drink is on promotion; and manufacturer. Complete datasets for all drinks were collected in December 2013 and October 2016. Data from 1281 Tesco drinks were collected from 2011 to 2016 using a combination of live and archived websites, 391 of which have more than three time points at which data was available. Full monthly data on all drinks from all six major online supermarkets is available from October 2016.

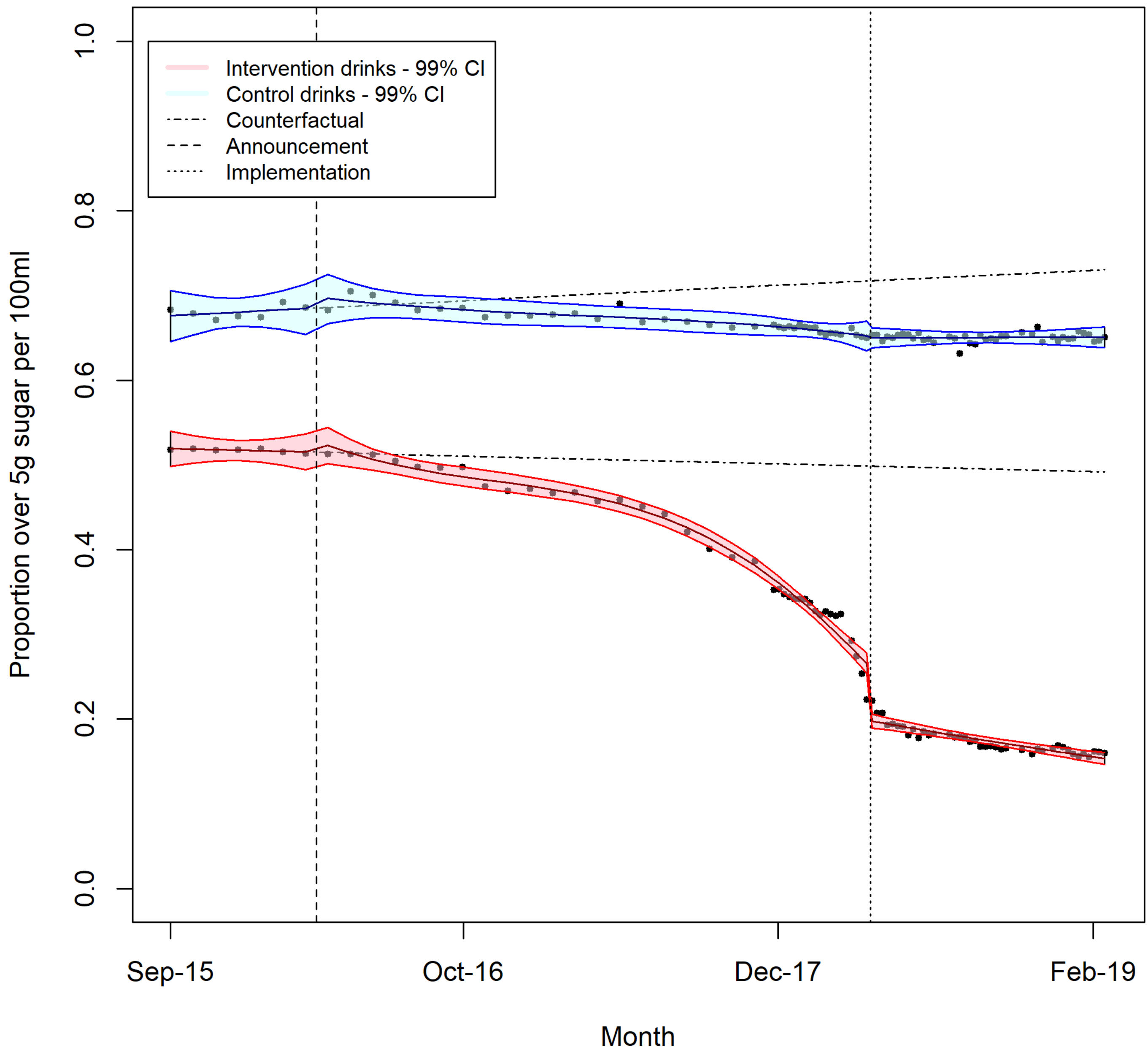
Outcome measures
We will have three outcome measures, one related to each of market diversity, formulation and price:
• number of products (e.g. Coca-Cola, not Coca-Cola 500ml bottle) available across six online supermarkets per month (market diversity)
• mean total sugar concentration in g/100ml per month (formulation)
• mean price (not sales-weighted) in £/100ml per month (price)

These will be considered overall and in each of the four drinks categories described above separately.

Study period and sample size
As described above we have some FoodDB data from 2013, with full data available from October 2016. This study will, therefore, include data from October 2016 (6 months after intervention announcement) – April 2020 (2 years after intervention implementation). Data are available per calendar month, thus providing 12 time points/year from full establishment of FoodDB onwards (October 2016), and a total of 42 time points in the study. Currently, we estimate that more than 1000 unique soft drinks products will be included per time point. This dataset therefore substantially exceeds current recommendations for minimum samples sizes for ITS analyses of at least 10 time points before and after the intervention, and at least 100 observations per time point.

Data analysis
We will conduct single time point, ITS analyses for each outcome overall in each of the four drinks categories described above separately. The unit of analysis will be the calendar month. As data is only available from after intervention announcement to after intervention implementation, we will include only one 'intervention' point – intervention implementation. As FoodDB is a database of products, rather than purchases or consumption, it will not be possible to study any differences by socio-demographic characteristics of purchases or consumers. Additional analyses stratified by supermarket price point may be possible e.g. as a student project add-on.


Tesco
Time points = 38
n = 53,938
Sainsbury's
Time points = 38
n = 16,875
Asda
Time points = 38
n = 22,070
Tesco
Time points = 64
n = 52,022
Sainsbury's
Time points = 64
n = 52,341
Asda
Time points = 64
n = 50,928
Morrisons
Time points = 64
n = 36,830
Waitrose
Time points = 64
n = 41,823
Ocado
Time points = 64
n = 68,529
August 2015 – September 2018 (monthly)
November 2017 – February 2019 (weekly)
BrandView dataset
Time points = 38
n = 92,883
foodDB dataset
Time points = 64
n = 302,473
Exclusions:
Price / product size data uncaptured
n = 2,272
Incomplete data capture
Time points = 1
n = 1,989
Exclusions:
Price / product size data uncaptured
n = 336
Incomplete data capture
Time points = 6
n = 24,879
BrandView dataset
Time points = 37
n = 88,622
foodDB dataset
Time points = 58
n = 277,258
Exclusions:
Remove data from Morrisons, Waitrose and Ocado
n = 133,186
Exclusions:
Price greater than £1/L
n = 6,202
Linking by name not possible
n = 31,008
Comparison dataset
Time points = 95
n = 232,694
Price dataset
Time points = 58
n = 240,048
Exclusions:
Overlap of datasets
Time points = 10
n = 23,057
Exclusions:
Product size greater than 3L
n = 6,832
Linking by name not possible
n = 30,687
Reformulation dataset
Time points = 85
n = 209,637
Product size dataset
Time points = 58
n = 239,739
Dataset collapsed onto time points and control / intervention status, with number of observations as outcome variable
Number of drinks dataset
Time points = 58
n = 116



Intervention drinks - 99% CI
Control drinks - 99% CI
Counterfactual
Announcement
Implementation
Proportion over 5g sugar per 100ml
0.0
0.2
0.4
0.6
0.8
1.0
Sep-15
Oct-16
Dec-17
Feb-19
Month